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# Combining Domain Expert Knowledge with Neural Networks for Predicting Corporate Bankruptcies

**By**

**M. L. Nasir B.Sc. M.Sc. ACIB RSA**

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This thesis is dedicated to my wife and children for their support throughout the completion of this study.

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# CHAPTER 1

# THE BACKGROUND

## 1.1 General Overview

Bankruptcy prediction problems are of great interest to researchers as well as creditors, and other interested parties that are likely to rely on corporate financial statements (David et. al., 1997). According to Duffy (1999), a large number of major public and private companies have gone bankrupt over the last few years (see Appendix B). Creditors have a personal stake in this decision problem in that they wish to identify perilous conditions of bankruptcy in the financial statements of their borrowers. Shareholders hold similar monetary concerns. Employees of the company may be concerned about the security of their employment and whether the company will survive in future. Company auditors, as a normal responsibility, must evaluate the financial position of a client to determine whether the company's operating ability is endangered (Beaver, 1966; Altman, 1968; Alici, 1995). For all parties concerned, including potential investors, it is essential that an objective opinion on the risk of bankruptcy can be formed as early as possible.

On the other hand, there are arguments for the direct and indirect benefits of corporate failure. Argenti (1976) argued for corporate failure's cleansing effect of competition and innovation. Financial analysts and economic theorists alike often cite the competitive environment for its weeding out of inefficient and poorly managed companies in order to perpetuate a healthy vibrant economy. Bankruptcy provides employment to thousands of insolvency practitioners, accountants, financial managers, and other professionals whose livelihoods are based on assisting failed companies and their employees. However, everyone else associated with a bankruptcy is worse off than if the failure had been avoided. For that reason, learning to predict impending bankruptcies is a responsibility shared by managers, investors, and employees alike.

Finding ways of trying to predict corporate failure as early as possible is clearly a matter of considerable importance to businessmen and other interested parties. For instance, if an investor or a financial analyst is able to predict a company on the path to failure before anyone else, he or she will be able to liquidate the investment or take some other evasive actions (e.g. obtain settlement of a debt) and so minimise losses.

Against this background there has been a growing urgency on the part of financial analysts, bankers, investors, corporate managers, and auditors to try to find better ways of predicting companies that are likely to fail before the event becomes irretrievably certain. This represents a demand, which many researchers have sought to satisfy by developing a number of different procedures that aim to give early warning of financial distress (Altman and Brenner, 1981).

What remains to be seen is that if there is a well established method of identifying failing companies in advance of their final collapse, one might reasonably expect investors and creditors to use the procedure and immediately act upon its predictions. Consequently, as soon as a new and accurate forecasting approach has been produced, one would expect it to be universally adopted. Todate, there is no universally accepted corporate failure predict model. Although the works of Beaver (1966) and Altman (1968) have been fervently adhered to throughout the world, their studies were based on certain restrictive assumptions. These assumptions will be identified in Chapter 2.

It is a little perplexing that other researchers (e.g. Odom and Sharda, 1990; Wilson and Sharda, 1994; Alici, 1995) seem to claim that they can successfully predict with some remarkable accuracy which companies are likely to fail and which are not. Indeed, it is not unusual to find that numerous researchers in the literature claim a remarkable success rate of over 90 per cent. It is not surprising that they were able to achieve this because of the methodology employed. The methodologies will be carefully explored in Section 3.5. So if this is the case, surely investors and creditors, and those agents, who work on their behalf, will undoubtedly search endlessly for a novel procedure that might give them a narrow advantage. If successful, financial analysts and their clients stand to make a lot of money from spotting failing companies in advance of their failure. The advantage being that those investors can quickly withdraw their investments in failing companies before bankruptcy becomes inevitable. It is therefore quite easy to believe that each innovation, which improves the accuracy of predictions, will be well worthwhile.

It would imply that in any one year, any analyst using one of the developed models that have been developed would correctly identify the 1471 or so companies that have gone bankrupt in the UK in 1997. The same analyst will also have a list of other companies that are likely to fail in the foreseeable future. Clearly analysts who might refer to the models to assist them in keeping a portfolio of good and bad companies would find themselves in an enviable position. It seems improbable, in fact, that such a situation can exist because of misclassification errors. Having said that, there is also the risk of incorrectly identifying a failing company as "healthy" when compared to those of incorrectly classifying a non-failing company as prima facie "bankrupt". The cost of misclassification errors can be catastrophic.

What has to be said therefore is that, where analysts refer to the models, they do so as a shorthand procedure for summarising data about a company. Given the problem of predicting corporate failure before it occurs, any analyst would use a failure model on one hand, and on the other, his own intuition. The ideal situation is to be able to maintain a portfolio of good companies even though the costs of incorrectly classifying a company would be constantly borne in mind. This is the dilemma for many corporate financial analysts.

Given the diversity of the businesses and the economy, from which the underlying financial data are derived, it appears that the classifications really just reflect the fact that a company is either good or bad. So those companies reporting losses or low profits and which they are burdened with large debts are more at risk than otherwise similar companies which are constantly reporting profit figures. However, which every way one interprets this scenario, the plight of a financially distressed company should be fairly obvious anyway, regardless of whether it eventually fails or not. What is vitally important is to able to spot those extremely unexpected cases that are bound to bring huge financial losses to the unwary financial analysts since the resounding effect will fall on his clients at the end of the day. It is expected that all user groups will rely on the advice they receive from their financial analysts.

There are substantive arguments for 'user needs'. The users of companies financial statements (e.g. investors, analysts, employees) can expect to receive accurate advice from their financial analysts about the financial status of the particular company. The investors and financial analysts can jointly operate quite successfully in an environment that appears to be very close to being informational perfect. The only costs involved would be to reward financial analysts for their special skills. It is also appropriate to focus more closely on what might be of interest to investors, creditors, company directors, auditors and other third parties. A successful prediction would encourage investors or creditors to put their money into specific high risk companies, knowing that some will fail but that overall rewards will more than offset the losses they will make on other investments and loans portfolios.

The case with the company directors is somewhat different. Company directors including the chairman have a stewardship role to ensure that the entity (company) remains in operational efficiency for the foreseeable future. It is the primary responsibility of company directors to ensure the particular company is run on sound footing and efforts should directed to make sure that this is the case at all times. On the other hand, it is also expected of company directors of being able to assess the likelihood of the company failing in the near future. It is incumbent on company directors to assess this likelihood so that urgent actions can be instituted to avoid a bad financial situation. The author now presents the scope of the thesis in section 1.2.

## 1.2 Scope of the Thesis

Recall that the previous section had mentioned one important research issue. This issue is that investors have a personal interest in bankruptcy prediction. It had been stated in the previous section that they do so in order to minimise their financial losses and the emotional sufferings that might follow. The important question that could stem from this is quite clear.

*Can a combination of domain expert knowledge and neural networks help to identify impending corporate bankruptcy?*

In order to address this important issue, investigative research in a number of areas was required. These areas included: neural networks; modelling techniques for predicting corporate bankruptcies; data from electronic sources; domain knowledge; and the evaluation of previous studies for predicting corporate failure. The results of these investigations allowed the research question to be successfully answered.

Most of the corporate failure prediction models reported in the literature are based on either using multivariate discriminant analysis or simple structures of neural networks to predict corporate bankruptcies (Nasir et. al., 1999; Coats and Fant, 1992). These two approaches will be considered in detail in chapters 2 & 3.

The objective of this thesis is to present a unique approach for predicting corporate bankruptcies which has used domain knowledge as its core in data selection, data categorisation, and data organisation in neural network architectures. The model which has been produced by this process has been evaluated firstly in terms of whether it provided a good model of corporate failure prediction, and secondly in terms of how well it could be regarded as a prototype system to support the process of corporate failure prediction. As such, the main research questions can be summarised as follows:

- Have many factors been implicated in the collapse of many companies?
- Do these factors occur in combination with one another?
- Choosing input parameters for network is very difficult, time consuming and central to the success of application modelling. Will the use of domain expert knowledge enhance the success of this application? This novel idea is a central issue for this research.
- Does a large volume of data covering the three groups, healthy, distressed and failed companies exist to conduct this experiment?
- Given the complexity of business activities, simple models of multivariate discriminant analysis and financial accounting ratios analysis have produced very

little results and unreliable as predictors of business failure. Does the ability of neural networks to infer complex non-linear relationships from data make them suitable for corporate bankruptcy prediction?

## 1.3 Research Methodologies

In pure science, such as chemistry, medicine and physics, it is almost certainly possible to conduct tightly controlled experiments in laboratories. For example, when testing a new drug it is common practice to treat a representative cross section of patients with a pharmaceutical compound; while another similar control group is given a placebo (Kohonen, 1988). The results can then be compared to see whether there any evidence that the new drug has any healing properties. However, when undertaking such experiment, it is vital that both groups for all intent and purposes identical, otherwise it is possible to draw incorrect inferences. Unfortunately, from time to time methodological errors become known, for example with thalidomide (Kohonen, 1988). On the other hand, in the social sciences for example, it is almost impossible to construct realistic experiments within a tightly controlled laboratory environment. However, there are reported cases (Beaver, 1966; Altman, 1968; Alici, 1995) where this had been possible provided two types of approach which employ inductive reasoning are satisfied:

1. those which are derived from readily observable data (such as accounting number, share prices, credit ratings, bankruptcies, etc); and
2. those which involve behavioural experiments where subjects express their own judgements and thus create the data which can then be the focus of analysis.

More commonly, researchers have to collect statistical evidence from real world events and use the data to test various hypotheses. It is the later approach that is commonly used in bankruptcy studies (Alici and Gifford, 1995).

Previous methodology in bankruptcy studies generally seems to be seriously flawed in two important aspects, and while these are generally acknowledged, the full implications are rarely examined in any detail. These implications will be discussed in this section. The first problem relates to the difficulty of collecting the data. Identifying data sources and collection for both listed and unlisted companies can be awkward particularly to defunct (failed) companies, since by their very circumstances it will often be well nigh impossible to obtain their records in any substantive form (Argenti, 1976). The second problem relates to collecting data for listed companies in particular. Since the number of failures among listed companies are relatively low compared to privately owned companies, data collection in this particular area is very difficult. To be successful therefore, it will be necessary to 'pool' the data over time to produce reasonable sized experimental examples and this process can be somehow problematic (Zavgren, 1983). The unwarranted assumption is that the underlying economic circumstances are the same each year. This is not always the case because companies activities changes across different periods (Bathory, 1984).

## 1.4 User needs

Although information relevant to failure identification can be viewed from a number of perspectives, however, it is probably best to concentrate on the user demand perspective. The typical decision-makers that will probably make use of financial information would seem to be equity investors, creditors and employees of the company. However, employees of the company have a unique interest in the security of their jobs. Yet typically they will be interested in the ability of their company to trade successfully and remain viable for the foreseeable future. The continuing existence of the company is paramount to their interest. Investors will hold portfolio of assets, and it follows that they will want to maintain a viable portfolio of their holdings and maintain the desired risk and return balance if one of the assets suffers a sharp fall in value. The risk to the user in this case is how diverse their holdings are and the amount of risk and return balance they are ready to maintain. The results for both the employees and other interested parties is that they will have an especially incentive to search for early warnings of potential bankruptcy, and the procedure which provides most information on future bankruptcies. Having said that, those users with well diversified investment holdings will also be anxious to get prior warning of an impending fall in the value of one of their assets, since this would enable them to sell out before others learn the news. What an investor, creditor, or employee really requires is prior knowledge of an event, so that evasive action, such as selling their investments before others learn about the event taken place. This is the unique position every investor would like to be.

In a typical informational efficient market setting, it is therefore seems intuitively unlikely that a model derived from financial variables such as financial ratios alone reflecting historic data will be of very much use. What would seem helpful is to have a model that is derived from a combination of both financial and other factors such as domain knowledge, economic (interest rates) and political factors so that the informational market setting can be complete. Beaver (1966) argued that there should be a means of identifying as early as possible a company's vulnerability to financial collapse and this may best be inferred from a model derived from a complete informational market setting. Thus, to the extent that financial analysts refer to failure prediction models when examining the accounts of companies, one might reasonably expect economic factor variables or at least anticipate that a combination of both will be captured in a model of this phenomenon. Undoubtedly, failure prediction models would appear likely to be of more value to investors and analysts in this direction.

Finally, in the context of user needs, there is another point (already alluded to) that needs to be made, namely, the relative cost of misclassifying a failed company as non-failed; and a non-failed company as failed. The former is known as Type 1 error and the latter is known as Type 2 error (Odom and Sharda, 1990). Altman et. al. 1994 argued that the cost of the latter should be far less than the cost of former. Studies in failure prediction will not eliminate classification errors, however, when a model is used for prediction purposes it will still be necessary to allow for the differential costs of classifying a failed company as non-failed and a healthy company as failed. Moreover, if analysts, creditors, investors and employees of the company accept predictions of a model, presumably all companies classified as failures should in fact fail, regardless of whether or not they would have done had they not been so classified Consequently those that bear the brunt of classification errors are the investors, creditors, and the employees of the company.

## 1.5 The Professional Significance of Study

The general problem of the study has intrinsic importance, affecting organisations, employees of organisations, and those people who have invested their money in the organisation. This study is important for the following reasons:

- Management needs a tool that enables them to analyse their own business situations and to monitor the performance of their enterprise in a dynamic way.
- The failure of a company is an event that can produce substantial losses to creditors, shareholders, employees, and senior management of the company.
- The emotional and financial suffering, which follows bankruptcy, is an event that is equally bad for management and investors.

The novel approach produced represents a unique contribution to the domain and would seem to advance knowledge in the field for the following reasons:

- A huge amount of data was used to train the network. The choice of data, and the pre-processing of data, was done using domain knowledge. The issues of missing values, missing data, financial outliers and creative accounting practices were dealt with according to experience in banking and commerce.
- The architecture chosen captures the underlying characteristics of the financial data selected.
- The type of architecture used was complex enough to capture all relevant relationships, although very difficult and time consuming to train.
- The architecture embodies most of the characteristics of the problem domain by taking into account the data trend over a three year period and putting more emphasis on current conditions and progressively less emphasis on distant (in time) conditions.

Although neural networks have been widely used in literature to predict corporate failure, the approach used for the study represents a unique contribution to the field of financial analysis.

## 1.6 Thesis Structure

Chapter 1 has explained the background to this research and introduced the research question. These issues are: which neural network paradigm are suitable for predicting corporate failure; can a combination of domain expert knowledge and neural networks provide an optimal solution; can the model produced be used as the basis of the future for predicting corporate failures?

Chapter 2 discusses previous research work on corporate failure prediction using traditional approaches. It is a critical review of those approaches favoured by accountants and financial analysts. The discussions here concentrated on those traditional approaches of corporate failure prediction such as univariate and multivariate techniques. This Chapter excludes any discussion on neural networks.

In Chapter 3 neural networks and their applications is presented. It describes previous works on corporate failure prediction using neural networks. This Chapter aims to provide the rationale supporting the notion that neural networks are suitable for predicting corporate bankruptcies.

Chapter 4 presents data pre-processing. It provides information on data sources and the collection procedure. A set of criteria by which data is selected for network training is established. Each selection is assessed to ascertain which of the criteria it meets and then judged how well domain expert knowledge can be used to organise data in the networks. In this Chapter, three levels of data normalisation procedures were considered. These levels and their importance are carefully explained in the chapter. The chapter also deals with the problems of missing values, hidden data, and creative accounting practices.

Chapter 5 describes neural network topologies. This Chapter presents a number of topologies. It firstly considered feed forward multilayered neural network (Topology 1) and then judged how well this topology will perform in solving the problem at hand. A number of alternative topologies (Topologies 2-5) that process time-varying patterns were considered and how well each can help solve the problem at hand. The contribution of this Chapter is that it describes a procedure for determining the optimal topology for predicting corporate bankruptcies where temporal tendencies exist. A practical procedure to implement the chosen topology is then outlined in great detail.

Chapter 6 presents the implementation of the study. In order to provide possible functionality of the neural network approach, the chapter addresses the software packages which are needed to perform the following tasks.

- data retrieval, analysis and transformation
- neural network architectures creation
- the organisation of data in the input layer
- paradigm selection
- the display of any information to the developer
- the submission of prediction for interpretation.

There are a number of software packages which have been especially developed to allow the use of large-scale data points, the building of complex neural network architectures and the selection of a particular paradigm for the investigation. This chapter identifies only those packages that are relevant to implement the study.

Chapter 7 presents evaluation of the study. It describes a distinction between a "good" and "bad" network. A full review of the methods for improving network learning is provided. A full evaluation of the "best solution" network is described and then provides reasons why this is the case in this context. Chapter 7 aims to show that a combination of inter-connected neural networks and domain expert knowledge will outperform conventional approaches of predicting corporate bankruptcies.

Chapter 8 presents a summary and discussion of the research findings. The discussion attends to the research issues and investigates the extent to which they have been met. This Chapter provides a summary of the research processes. The limitations of the research are identified, as are the implications of the research. Finally, this Chapter concludes with suggestions for future work.

# CHAPTER 2

# REVIEW OF PREVIOUS WORKS ON PREDICTING CORPORATE FAILURE

## 2.1 Introduction

The previous chapter examined a number of background issues concerning bankruptcy studies. In particular, it was first necessary to mention that business failures, including the corporate bankruptcy phenomenon, are sobering economic realities reflecting the uniqueness of the British way of sudden corporate collapses. Most concerned investment analysts and other interested parties (e.g. creditors, and employees), view the unsuccessful business venture as a negative economic event both to the principals of the failed company and the society in general. The larger the bankrupt's interface with others, the more profound the effect. In addition, a number of methodological issues that need to be considered had been discussed. It was stated in the previous chapter that before engaging in bankruptcy studies, it is highly desirable to establish by deductive reasoning those factors that might be reasonably expected to bring about the failure of a company. It was also mentioned that it is necessary to explain by inductive reasoning why in practice companies do fail.

The primary purpose of this chapter is to describe in some detail the procedures used by numerous researchers to examine the characteristics of financially distressed companies and to review the empirical evidence. Although a large number of studies have been produced to explain the underlying positive theory which might explain why many companies fail, and the procedures used to predict failure, it will nevertheless be convenient to regard them within that context.

Financial analysts have a long tradition in corporate evaluation, by simply referring to certain numbers, known as financial ratios, from companies' financial statements. These selected ratios are used to gauge business performance over a defined period. However, the nature of the analysis is essentially 'univariate' that is, the financial ratios are examined *seriatim* one-by-one. This is the Beaver's (1966) initial approach.

Consequently, Beaver's work does not allow for interactions between financial variables (or financial ratios) except judgementally of course. Potentially more powerful 'multivariate' analytical procedures can be applied which will allow for the simultaneous interactions between financial variables.

The aim of this chapter is to consider various statistical approaches that have been proposed for predicting corporate failure. In the first instance, this means reviewing the 'traditional' methods of interpreting the financial statements of companies. However, the conventional approach is not the only way in which financial ratios can be examined or analysed. It is also possible to apply more systematic procedures to analyse financial data and thus try to obtain a picture of company's performance, its current financial position and future prospects. One such iterative model is the use of neural networks which will be considered in Chapter 3. It is the view of this chapter therefore to concentrate on the so-called statistical (traditional) approaches.

This chapter proceeds as follows: Section 2 attempts to define the term corporate failure. In section 3, the general causes and symptoms of corporate failure are explained in some detail. Financial ratio analysis is presented in section 4. Section 5 presents empirical studies. Section 6 presents non-financial indicators. A summary is provided in section 7.

## 2.2 What is Corporate Failure?

Corporate failure defies precise definition (Beaver, 1966, Altman, 1968). Any attempt to define the term precisely would fail (Kharbanda and Stallworthy 1985), and would make any model based on such precise definition unworkable (Lev and Sunder, 1979; Laitinen, 1991). Most companies fail, however, because of a combination of causes (Taffler and Tseung, 1984). The actual causes of corporate failure are complex, multivariate and interconnected (Taffler, 1977, Nasir et. al., 2000).

Corporate failure in some senses obviously encompasses 'bankruptcy', for a company it effectively means a creditor's liquidation or the appointment of a receiver. Altman and McGough, (1974) argued that the net could be drawn more widely to embrace situations where there is evidence of 'protracted financial distress'. It is therefore useful to list a spectrum of potential indicators of corporate distress. This will start with situations where there is general agreement on what constitute bankruptcy and working down to various other circumstances which can be regarded as general indicative of an impending bankruptcy. Smith, (1966) and Slatter, (1984) provide the list succinctly below:

- creditors' or voluntary liquidation, appointment of a receiver;
- suspension of Stock Exchange listing;
- going concern qualification by the auditors;
- composition with creditors;
- protection sought from creditors;
- breach of debt covenants;
- a bad economy;
- hostile take-over;
- a rise in inflation rates;
- a rise in interest rates;
- a rise in inter-bank borrowing rates;
- dramatic fall in company's share price.

Most of the corporate failure studies (Beaver, 1966, Altman, 1968, Alici, 1995) have concentrated on the first few items in the above list, although some of the others may be taken as indicators of impending difficulties.

Corporate failure can best be defined precisely after the unfortunate event had taken place. This is the best way to attempt a precise definition of the term (Beaver, 1977; Nasir, et. al., 1999). The case of Barings Investment Bank Plc is a good example. The bank collapsed in 1995 with a loss of £885 million due to the action of a single equity trader (employee) (Duffy, 1997). In this case, corporate failure is defined with respect to Barings Bank scenario only. Another example is the case of Bank of Credit and Commerce International (BCCI). The Bank collapsed in 1990 because it had represented various assets on its balance sheet that cannot be accounted for physically

(David et. al., 1997). In any case, these assets were reported in bank's annual financial statements and those assets did not exist. It is regrettable to say the least that BCCI collapsed with an estimated debt of £25 billion when clearly the bank had reported £75 billion worth of assets. The bank had engaged itself in money laundering activities across international borders. So, when the money laundering activities were discovered and frozen by the United States Government, the veil of illegalities were lifted and the bank collapsed with huge liabilities (Duffy, 1997). In this case, corporate failure can be defined with particular reference to BCCI alone. The fact that many factors are always implicated in the collapse of many companies makes the definition of the term "corporate failure" almost impossible.

### 2.2.1 The meaning of 'prediction'

Many studies published so far (e.g. Beaver, 1966; Altman, 1968; Alici, 1995; Taffler, 1982) on corporate failure specifically refer to 'predicting corporate bankruptcy'. However, it has become necessary to deal with another semantic issue, which is rarely addressed in the literature – namely, what exactly is meant by 'prediction'. Argenti (1976) argue that the term prediction has two distinct meanings. The studies provide the distinction as follows:

Prediction can mean 'identification' – i.e. in a narrow statistical sense it should be possible historically (or 'ex post') for a given population of companies to predict (identify) which businesses went bankrupt and which did not. Altman argue that such an autopsy can be useful as a way of enhancing understanding of the phenomena which characterise corporate failure.

Prediction can mean 'forecast' – i.e. it implies that is should somehow be possible to distinguish in advance (or 'ex ante') those firms which, within a given time span, will fail and those that will not.

From this study point of view, it is the second that is of interest in particular. Essentially, it is believed that it is possible to discover a way of successfully discriminating between failed and non-failed companies. Consequently, as soon as this possibility has been highlighted that the accounts of a particular company resemble that of a previously failed company, presumably all interested parties will be advised accordingly. This is the essence of prediction. However, if a failure 'prediction' model is successful, not only will it be self-fulfilling to the financial analyst; but also, it would help investors to minimise financial losses. Of course, in practice, there may be institutional barriers, which may prevent financial analysts from making a near perfect prediction. Nevertheless, it is desirable to have a corporate failure prediction model.

## 2.3 The General Causes of Corporate Failure

This section of the chapter will be concerned primarily with a review of the causes and symptoms, which precipitate bankruptcies. These conditions are generally mentioned in the literature (e.g. Beaver, 1966; Altman, 1968; Alici, 1995) by numerous researchers in bankruptcy studies. The relevance of this section is that it represents the basis of which many of the various bankruptcy studies are derived.

It will be useful now to distinguish between causes of failure from symptoms of failure. A cause is something that produces a result, whereas a symptom is a sign that something has happened, or is about to happen. The review and interpretations of a company's financial statement over a number of years will provide a useful routine for picking up danger signals, and it is the responsibility of the financial analyst to be constantly alerted to them. It is rare for bankruptcy to occur completely "out of the blue", although some cases exist as in the case of Barings Bank which had been mentioned earlier. There will be a preceding period of months or even years during which time the signs are there to be seen and interpreted. It is not always easy to identify unequivocally the symptoms of failure, but it is equally important to predict failure using a company's past financial history and any other available information in public domain. What follows are some of the causes and symptoms of corporate failure popularly discussed in literature which needs to be explained in some detail.

Financial failure occurs when the enterprise has chronic and serious losses or when the company becomes insolvent with liabilities disproportionate to the assets (Altman et.al., 1994). The generally accepted causes of corporate bankruptcy are poor management, autocratic leadership, technocrats turned businessmen, failure to operate successfully in the market place, or inability to pay debts when due (Betts and Belhoul, 1987). These factors have all been implicated in the collapse of many companies.

What happened to Azil Nadir and Polly Peck? Was this case an example of the dominant and autocratic chief executive, which characterises many failing companies? Robert Maxwell was the head of one of the most powerful publishing corporations in the western world in the 1980s, Maxwell Corporation. He died in 1991 and his empire collapsed shortly after. The revelations about financial mismanagement after his death were catastrophic. He was renowned for his authoritarian approach to managing his business. Everything was centralised in his hands, and little is left of his empire today.

Many of the most successful companies have been built up largely on the efforts of an autocratic chief executive, for example, Trust House Forte, under Sir Charles Forte. As long as such companies remain financially viable, every one points to the vision and leadership of the chief executive as an essential factor for success. However, as soon as trouble occurs, that same individual is blamed for the trouble.

In today's vulnerable and volatile business climate, corporate liquidations and reorganisations are common occurrences among large corporations including household names. For example, Dewhurst, Britain's largest butcher's chain collapsed in April 1995 because of an unsettled business climate, and falling in demand. The sudden collapse of Britain's biggest butcher's chain (Dewhurst) highlights the dramatic decline of what was once thought to be a very good company (Duffy, 1997).

A study conducted by Jones (1987) concluded as follows:

"A company was said to be chronically insolvent if it became increasingly unable to meet its financial obligations over two or more accounting periods. The company was, accordingly, unable to generate enough cash to meet trading troughs without incurring further losses."

Jones, (1987) argued further that a company's inability to meet its obligations as they fall due may have existed over some years and may have increased. This could be verified by looking into some historical data of the company. Furthermore, a cursory look at the company's financial statements would confirm that obligations could not be met at the date on which the accounts were made up and, furthermore, that sufficient cash did not appear to have been generated to cover existing much less future downwards trends in trading. These are obvious symptoms of bankruptcy.

Casey and Bartczak, (1984) identified an important cause of corporate failure. They argued that a company may have become historically insolvent based on its published financial statements. However, what is the probability that its management can generate enough cash to meet pressing obligations, reschedule others, and survive expectable trading troughs over the next accounting period without outright collapse? The answers to this question lie in the mind of the reader of the company's financial statements.

Smith in his book "Corporation in Crisis" (1996) provides a general guide to the causes and symptoms of corporate failure. He believes that centralisation is a wellspring of crisis and the central cause is the boss. For Example, Henry Ford still ran his company long after it had passed the size that any human being could handle it alone. He failed because he refused to change his methods, the company was too big to handle, and he created a massive cost empire, which went out of control. The company was then taken over and is now being run piecemeal by other subsidiaries in various countries including Ford Motors UK Ltd.

Casey (1980) identified some causes of failure as giving a company to people who don't know where they are going, men with insufficient knowledge, managers running businesses on ageing products.

Dambolena (1983) said a company generally fails if it does not keep abreast of information technology. Dambolena (1983) described causes of corporate failure by using the Lancashire Engine Company as the basis of his study. There was no summary and conclusions but he added ten further dimensions to the popularly known causes of corporate failure. According to Dambolena (1983), the Lancashire Engine Company ran out of cash because of its endless development towards attaining technical perfectionism. His description is a good example of what happened to Cyril Lord. Lord was a powerful personality and his knowledge of carpet manufacture was unrivalled. His boundless energy took him to setting up ten businesses within ten years, but all failed because as Dambolena (1983) says, Cyril Lord lacked management depth and had no full time finance director. In 1988, he boasted that he was making £2m profits annually when, in real terms, he was indeed making losses from all his businesses.

Kharbanda and Stallworthy (1985) identified a symptom of failure as a condition where the management of a company have seen for years symptoms of failure but may not have recognised it until such a time that it slips into chaos, and bankruptcy is irretrievably certain. It was argued further by the authors that customers would have noticed the company pressing them to pay their invoices; suppliers would have noticed the company delaying payment to them; employees would have noticed the lower pay packets, the dingy offices and the delay in maintaining plant and the postponed expenditure authorisations.

Keasey and Watson (1987) described a major symptom of corporate failure as a panic measure instituted by a desperate company to pay in a cheque so that wages of employees could be paid at the month end. Slatter (1984) asserted that there are plenty of symptoms and failure to recognise them well in advance are a well spring of crisis.

From what has been so far in this section, it appears that it was possible to be confident of diagnosing trouble from even a cursory study of the published financial statements of desperate companies. One of the phenomena we have seen recently is the case of Bank of Credit and Commerce International (BCCI) and Dewhurst as mentioned earlier. The next section will now look into the reasons we should predict corporate failure.

### 2.3.1 Why Predict Corporate Failure?

The failure of a business enterprise is an event, which can produce substantial losses to creditors, shareholders, and employees of the company (Nasir et. al. 1998). Management needs a tool that enables them to analyse business situations and to monitor the performance of their enterprise in a dynamic way using robust techniques to warn them well in advance of a potential crisis. Armed with a robust forecasting technique, management can take action that is relevant to the problems revealed, and can refrain from irrelevant action, perhaps costly and damaging, which they otherwise might have taken in the absence of robust forecasting techniques. The benefit of this is that it would provide ample warning to management, investors, employees, shareholders and other interested parties who wish to avoid losses and emotional sufferings.

What is important for this section is the sheer volume of company failures that have occurred in the UK over the last few years (see Appendix B). The number of bankruptcies in the UK is therefore a matter of great concern particularly to those investors who might have invested their savings in the particular company. The consequences that follow company bankruptcy can be catastrophic. It is therefore important that we able to identify bad companies well in advance. The sheer volume of research works in this area explains the importance of the topic.

## 2.4 Traditional Financial Ratio Analysis

This section will be concerned with the use of financial ratios as predictor of corporate failure. It is difficult to provide an exhaustive explanations of the significance of financial ratios in any thesis, however, what is provided in this section should be taken in that context.

From a previous lending banker perspective, financial ratios are traditionally classified into six main groups. Table 2.1 lists the groups and specifies their focus.

| Type | Characteristic |
|---|---|
| Liquidity | Ability to meet current liabilities |
| Debt | How the company is financed |
| Activity | How effectively assets are used |
| Profitability | Compares profit to sales and investments |
| Growth | Where the company is going |
| Value | How the company is judged by the market |

**Table 2.1 Six Main Groups of Financial Ratios**

Although the table shows each type, there are more than several financial ratios in each category depending on the type of industry and definition used. Some ratios have been put forward as better explanatory variables in predicting corporate failures (Taffler, 1982). These explanatory variables are listed in Table 2.2. These ratios are found in the liquidity, debt activity, and profitability categories.

| | |
|---|---|
| Liquidity Ratios | |
| Net working capital | Current assets less current liabilities |
| Cash flow versus current liabilities | Net income plus depreciation and other non-cash expenses divided by current liabilities |
| Debt Ratios | |
| Cash-flow coverage | Cash-flow divided by fixed charges, including interest and dividends |
| Return on Capital Employed | |
| Periods interest earned | Income before interest and taxation Divided by interest charges |
| Short-term debt to assets | Current liabilities divided by total assets |
| Activity Ratios | |
| Stock Turnover | Sales divided by Stocks |
| Average Collection Period | Sales debtors divided by daily sales |
| Profitability Ratios | |
| Profit margin | Net income divided by sales |

**Table 2.2 Bankruptcy Detecting Financial Ratios**

The above financial ratios are regularly mentioned in literature as better explanatory variables for forecasting corporate bankruptcies. However, popular they may be, their selections should depend on the nature of the problem to be solved and even more importantly, the domain knowledge of the financial analyst.

Financial ratios are easy to produce and use. The information that is needed is usually found in the financial statements of companies made public in annual or quarterly company reports, or by computer time-sharing services that have data banks which can be downloaded through The London Stock Exchange. Financial advisers and lending bankers constantly utilise financial ratios to monitor the companies they follow. However, whilst this is a rather common sense approach, relying on financial ratios alone can have certain limitations which will be explained in section 2.4.1.

The author will now discuss the use of financial ratios and their importance. Financial ratios can be used in two broad ways:

1. to compare one company itself over time
2. to contrast several companies in the same year.

Argenti (1976) argues that the former approach identifies when a company's ratios change. Change may occur for any of three reasons: first, the company's financial position has weakened, second, its financial condition has improved or thirdly, in response to an external change, the company has made an internal response. To find out if a change is due to external events, inter-company comparisons are conducted. When, for example, every company in an industry experiences a downturn in sales, instead of concluding that one company has lost control of the market over its products, it may be better assumed the industry is experiencing a bad period.. According to Altman (1968), when such a change occurs, bankruptcy does not necessarily follow. The best analogy to explain why financial ratios predict more troubled companies than actually exist is to consider the work of the local weather forecaster. Sometimes, despite seemingly perfect conditions, a storm will suddenly strike in an area. At other times, a projected blizzard fails to arrive because some unexpected event intervened. To do his or her job, the weather forecaster must always predict a storm whenever it seems likely to occur. When the storm vanishes, the forecaster reacts in the same way as when an unexpected storm appears: apologise and carry on with the job. The same holds for financial ratios: they predict some failures that are avoided and entirely miss other failures that occur (Lev and Sunder, 1979).

The financial ratios listed in Table 2.2 are now discussed briefly. Recall that the first four ratios as shown in Table 2.1 are concerned with the company's ability to meet its creditor's expectations (i.e. ability to pay debts when they become due). Creditors expect a company to pay its debt when they fall due. It had been stated previously in Section 2.3 that the inability of a company to pay its debt when due is a symptom of failure.

Net working capital, the difference between a company's current assets and current liabilities, measures the amount of money that would be left over if a company decides to liquidate its current assets at face value (i.e. at realisable value) and use the proceeds to pay off its current debts. Although it is doubtful that current assets could be sold at their face value in times of crisis (hasty sale), net working capital nonetheless constitutes a good indicator of financial health (Beaver, 1968). Beaver (1966) considers that when a company finances a large proportion of its current assets with long-term debt, it is unlikely that a short-term liquidity crisis will ever arise.

The cash flow-to-current liabilities ratio is an alternative approach to gauging the ability of a company to avoid liquidity crisis (Argenti, 1976; Taffler, 1982). Current liabilities must either be renewed (Barnes, 1987) or refunded (Taffler, 1982). A company must demonstrate the ability to renew or refund current liabilities very quickly otherwise creditors will hesitate renewing it. The paradox (one known from experience) is exactly the one many people have personally experienced with their credit cards. Banks would almost certainly respond to a request for a higher credit limit if the cardholder can pay off large part of his or her debt and then it will raise the limit. The bank is really telling the cardholder to prove that he or she is creditworthy by paying off the debt. The story is the same for companies. Companies in a liquidity bind are asked to repay instead of renew their obligations.

Cash flow is the money that the company accumulates throughout its trading year after paying debts that fall due (Altman, 1968; Alici, 1995). The higher the ratio of cash flow to current liabilities, the more likely that the company is able to renew its current debt and pay off a portion of it.

The cash flow coverage and times interest earned ratios are similar to the short-term ratios except that they monitor total debt instead of current liabilities (Taffler, 1982). The higher the ratio, the greater is the flows of money into the company relative to its obligations to pay interests, dividends, and repay debts. Thus, the higher the ratios, the less likely the company is to become a bankruptcy risk (Berry and Treiguiros, 1991).

The final three ratios, stock turnover, the average collection period, and the profit margin give warnings of worsening financial condition. They are not indicators of imminent collapse; however, if they persist, then collapse is more likely (Blum, 1974).

This particular section has been looking at numerous studies on financial ratios (although succinctly), however, there is yet another important phenomenon that has been constantly ignored by leading researchers. Section 2.4.1 will be addressing this important phenomenon.

### 2.4.1 Using Common Sense

Using a little common sense may well be the best (supposedly) predictor of bankruptcy. This little experience is derived from the very awareness of financial accounting ratios. Those applying the common sense method do not need sophisticated equipment and will not have to digest every financial report ever published by a company. Instead, the method requires being attuned to the realities of the environment in which many businesses are operated. Table 2.3 lists both the financial and product signs to watch for with the common sense technique.

| Financial or company signs |
|---|
| The company announces that it will be using a new accounting (auditors) firm<br>The company has developed a new banking relationship.<br>A management dispute surfaces in a public forum.<br>Members of the board of directors suddenly resign.<br>The borrowing credit lines are suddenly reduced.<br>Hasty selling of stocks to pay major creditors.<br>A major write-off of assets takes place.<br>The company is seen disregarding the cash flow cycle, level of current assets and short-term debt. |
| Product signs |
| New competition enters the market.<br>Other companies seem to be selling products that are a generation ahead.<br>The research and development budget is proportionately less than the competitions.<br>Friends and neighbours are recommending another product. |

**Table 2.3 Common-sense Bankruptcy Detectors**

Altman (1968) argue that some bankruptcies evolve suddenly. The majority seems to develop over a span of two or three years. Most have a multitude of causes, each of which contributes its share to the company's ultimate demise. Taffler, (1982) suggested that the common-sense approach avoid being stuck with fine nifty gritty details. Argenti (1976) suggested that if a company is seen changing auditors, a blatant sign have been received. It is suggested that the financial analyst must investigate further by examining the details. In some cases, this investigation discloses a dispute between the accountants and the company, the result of which is that the company's true financial health is in serious doubt. It could be, as argued by Argenti (1976) that the company's true financial health is worse than had been disclosed in the financial data.

It is commonly agreed that the common-sense signs for detecting corporate failure should be treated like church bells or dinner whistle. When one hears them, it is time to do something. Whether trouble is located or not, the common-sense sign has performed its function: it has forced one to be aware of what is really happening. The limitations of financial ratios are now presented in section.

### 2.4.1 Limitations of Traditional Financial Ratio Analysis

Although there are several limitations with the use of financial ratios for the predictions of corporate bankruptcy, only a few will be discussed. Other limitations not mentioned here will be mentioned when discussing empirical work on traditional ratio analysis. There are a number of problems associated with the use financial ratios:

- The figures used in the ratios are often taken from companies' financial statements, which show the position at a particular period in time. However, these figures rapidly get out of date and also, the companies' financial position may have changed quite significantly when the financial analyst examines the figures some months after the financial statements had been published.

- Financial ratios are inherently unstable. For instance, different analysts in deriving at a denominator can consider several factors. This can easily happen fortuitously if for example, two ratios being compared reflect different position in an operating cycle. However, it is expected that the experienced financial analyst should be able to handle a situation like this quite comfortably.

- Ratio analyses are based on historical data, which are only relevant to the period under investigation. It is therefore difficult for any analyst to come out with any meaningful results based on these figures without making assumptions.

- The calculation of ratios and their interpretation is time consuming and costly. Human experts would normally do the interpretation on a piecemeal basis.

- Financial ratios are based only on what management decides to publish in their annual financial statements. Any interpretation is judged on what is provided.

- Since financial ratios are always in abstract or discrete form, it is difficult to generalise from their calculations.

### 2.4.2 The importance of financial ratio analysis

Ratios are common-size reductive devices, which allows analysts to reduce both extremely small and large financial data to lowest numbers or multiples. For example, a comparison of £345,678 to £567,902 would be expressed by the ratio 0.60%, which is more easily assimilable. They highlight dangers whilst summarising.

Financial ratios can be used to:

- Assess the current performance of a business, on a monthly basis. This information is usually provided for internal use only and can be viewed by managers within the business. Senior managers of the company will therefore view this information on a departmental basis and take necessary action to improve performance.

- Assess future performance of a business in order to take certain strategic actions for the benefits of the business. The ratios calculated will point the direction as to whether a short-term or long-term strategic action is needed. Managers don't often ignore these indicators.

- Compare performance with that achieved by competitors, on an annual basis. Financial ratios enable management to look into the achievement of their competitors.

- Compare the performance of other companies within the business and decide which part of the business should be shut down if found unproductive.

- Financial ratios can be effectively used as a tool that enables management to analyse their business situations and monitor the performance of their competitors. Armed with the information provided, managers can take certain corrective actions that are relevant to the information revealed.

- Ratio analyses enables management to monitor the performance of their own suppliers, which may be critical to their own operations thus allowing them to look for supplies elsewhere. It also enables management to analyse the accounts of their own debtors so that supplies to vulnerable debtors can be monitored and in some instances stopped. The importance of financial ratios cannot be over emphasised.

## 2.5 Empirical Studies

Empirical studies in predicting corporate failure have been developed by academics on a rather different basis to the traditional form of financial statement analysis described in the literature (Bathory, 1984). Accountants and bankers tend to rely on financial ratios alone in assessing whether the financial statements of a company resemble that of a previously failed company (Beaver, 1966; Altman, 1968). Essentially accountants and bankers collect the financial statements of the company under investigation for up to five years previously. The financial ratios in the accounts are then examined *seriatim* one-by-one (Kharbanda and Stallworthy, 1985). Since this long tradition has its shortcomings, numerous researchers have produced several alternative models. These alternative models are now discussed.

### 2.5.1 Univariate Models

A critical review of literature in this domain suggests that Beaver (1966) studies began with the development of single ratio, the current ratio, for a single purpose; the evaluation of credit-worthiness of companies. Using a paired sample analysis, with size and industry type used a basis for pairing, he found overwhelming evidence of differences in the ratios of failed and healthy companies. To test the predictive power of this univariate approach, he used a dichotomous classification technique, and found the cash flow to total debt to be the best predictor of failure five years preceding bankruptcy.

Beaver (1966) considers that liquidity is a good test of solvency. In order to test this concept of ratio analysis Beaver initially identified 30 ratios for a population of 79 pairs of companies, and the ratios were allocated to six groups reflecting different financial characteristics. The best discriminator were working capital funds flow/debt (which identified the companies correctly in 90 per cent of cases one year to failure); and the income/total assets (which had a success rate of 88 per cent at a similar stage). The proportion of misclassification increased as the years prior to bankruptcy were increased.

There have been relatively few univariate studies since after Beaver's (1966) studies. However, Casey and Bartczak (1984) conducted a study on the discriminatory power of a single ratio, 'operating cash flow' and other cash flows. In this study a survey showed funds flow indicators as a key indicator of bankruptcy risk. Casey and Bartczak found that they could correctly classify 90 per cent of bankrupt companies one year prior to collapse and 92 per cent two years before. However, the discriminatory power was far worse for non-failing companies, namely, only 53 per cent and 44 per cent for the corresponding two years prior to bankruptcy of the matched companies. Academics undertaking bankruptcy studies have overwhelmingly chosen to employ multivariate methods of analysis, however, this will be explained in more detail in section 2.5.

The limited success of the univariate methods of analysis could be attributed to several factors. In summary three main reasons are identified.

- The simple methodology enables only a single determinant (univariate) from a large sample of financial ratios to be analysed at the same time. However, many factors are always implicated in the failure of most companies. In addition to this point, classical techniques for decision making and prediction do not work well for many applications with restricted sample sizes. A univariate approach is only capable of picking out trends, and will have considerable difficulty in modelling cycles that are by no means repetitive in amplitude, period or shape.

- Moreover, possibly even more important, the structural relationship between predicting failure and its causes changes over time. These changes can be abrupt and catastrophic. The failure of Barings Investment Bank in the UK is a typical example. This phenomenon of unstable structural parameters (financial variables) in corporate failure modelling is a special case of a general fundamental critique of univariate method of analysis.

- Many of the techniques that govern the predictions of company failure are, almost invariably, qualitative or fuzzy requiring judgement, and hence by definition are not susceptible to purely quantitative analysis.

Despite the above shortcomings financial ratios remain popularly used by accountants today (Nasir et. al., 1999). Beaver's univariate methods of analysis did not enjoy much popularity because it lacked depth and accurate predictive power (Altman, 1968).

### 2.5.2 Multivariate Models

Professor Edward Altman began the work in the field of corporate bankruptcy prediction using multiple discriminant analysis (MDA) in 1968. It was thought that the univariate methods of analysis produced consequential multiplicative errors. Altman (1968) improved on Beaver's univariate method of analysis by proposing the multivariate approach, which allows for the simultaneous consideration of several financial variables in trying to identify impending bankruptcy.

Multiple discriminant analysis is a statistical technique used to construct classification schemes so as to assign previous unclassified observations to the appropriate group. Altman based his work on groups of appropriate financial reports extracted from companies' accounting statements. His work (known as Altman's Z-Scores) was expressed as follows:

$$\mathbf{Z = 0.012X_1 + 0.014X_2 + 0.0033X_3 + 0.006X_4 + 0.999X_5}$$

In which **Z** = the overall solvency index and $X_1$ to $X_5$ are the independent variables.

$X_1$ = working capital to total assets

$X_2$ = retained earnings to total assets

$X_3$ = earnings before interest and taxes to total assets

$X_4$ = market value of equity to book value of total assets

$X_5$ = sales to total assets

Altman used a MDA programme to calculate the numeric values as shown above. The Z values were used to classify companies as either bankrupt or non-bankrupt. Where the Z score was below 1.81, the company was considered to be failing; where it was above 2.99 it was considered healthy. It was soon noted, however, that Altman's original work would not predict accurately when applied to UK companies because market capitalisation of U.S Corporations and UK counterparts varied sufficiently. These findings lead to other academics to investigate MDA methods of analysis further.

Deakin, (1976) modified the Altman model to include the 14 best ratios identified by Beaver (1966) in his univariate study. The sample had been 32 companies which had failed between 1964-1970, and the control group of companies was selected on a random basis, but matched by size, industry and year. Deakin also used a version of MDA, which assigns a probability of membership to the failed and non-failed groups based on its Z-scores in previous studies. However, Deakin's model performed less well against a random sample of 11 bankrupt and 23 non-bankrupt companies.

Liz (1972), using a sample of quoted manufacturing and construction companies, matched by industry and asset size, established a model known as the Zeta Analysis.

The Zeta Analysis model with MDA - determined ratio coefficients was:

$$\mathbf{Z{=}0.063X_1 + 0.092X_2 + 0.057X_3 + 0.0014X_4}$$

Where: $X_1$ = Working capital/total assets

$X_2$ = Earnings before interest and tax-total assets

$X_3$ = Retained earnings

$X_4$ = Net worth/total debt

It should be noted that the above model is a slight modification to the original work carried out by Altman; and actually, there is very little difference as to their significance and meaning.

. In 1974, Richard Taffler's research on the ex ante predictive ability of the MDA-based approach developed a five-ratio model of the following description:

$$\mathbf{Z = c_O + c_1X_1 + c_2{+}X_2 + c_3X_3 + c_4X_4 + c_5X_5}$$

Where: $X_1$ = Earnings before interest and tax/total sales

$X_2$ = Total Liabilities/net capital employed

$X_3$ = Quick assets/total assets

$X_4$ = Stock turnover

With $c_0$ to $c_5$ as the weights.

Taffler's model was well respected in the UK and very comparable to the work of Altman. Since his work is considered as a benchmark in the UK, it is worth looking at this model in some detail. The stages are therefore mentioned succinctly below:

- His first model was developed in 1974 as mentioned earlier and was based on a sample of 23 companies which had failed over the period 1968-1973 together with a control sample of 45 companies. Taffler used principal component analysis (PCA) and stepwise procedures to select 50 financial variables, normalised where necessary, to derive a model with just five variables. Incorporating prior probability odds of 1:10 (failed:solvent) in the model, the procedure discriminated extremely well in the last year before failure, but far less well for previous years.

- Subsequently the model was refined (Taffler, 1982, 1983). The bankrupt samples was expanded to 46 listed manufacturing companies that failed over the period 1969-1976, the companies being matched by industry and size another 46 companies. After considering 80 ratios applying PCA, the final variables selected were only six. Of the 14 per cent Taffler considered were at risk, 25 per cent went into receivership or been bailed out by the government. Another 11 per cent had been rescued in take-overs, and 7 per cent had closed their businesses altogether.

- Taffler (1984) subsequently developed models specifically for companies in the distribution sector and for private companies. The samples for deriving the model were 22 failed and 49 healthy listed companies. The financial ratios selected using PCA had been only four (cash/total liabilities, debt/quick assets, current liabilities/total assets, and the non-credit intervals). Allowance for possible misclassification costs was made and the model again performed very well in the year immediately before bankruptcy. The work of Coats and Fant (1993) provided a savage attack on Taffler's models for lack of practical depth and that they had been based on very small population samples. Taffler's approach of using principal component analysis to reduce financial variables from 80 to 6 variables in his model was criticised by (McFadden, 1976). The author considers that deriving models with few variables can produce models which are less effective in application. However, the practicality of such models should be taken only within the context of the samples selected.

Blum (1974) constructed an MDA model to assess the probability of corporate failure, the author sample comprises of 115 companies which had failed between 1954 and 1968 and 115 non-failed companies matched by industry, size and year. Twelve financial variables were selected to test the model. The model predicted very well against test sample of data one year prior to failure, but the error increased very rapidly in years 2, 3, 4, and 5. The project was later abandoned.

Blum (1974), Tisshaw (1976), Bathory (1984), Breiman et. al., (1984) Argenti (1985) and have developed other MDA methods of analysis. All these authors indicated that total predictive power is effective using fewer rather than many variables. Bathory's (1984) model is a multi-purpose analytical tool that is worth mentioning here. It was designed to be used across all industry sectors save banks and insurance houses. The model is used with best effect in conjunction with companies' standard credit analytical routines. The model did not go very far and was quickly derided by leading commentators (Eisenbeis, 1977) for lack of practicality.

#### 2.5.2.1 Pitfalls of the MDA Models

The multivariate discriminant analysis had its difficulties, and it was criticised on various grounds by Joy and Tollesfson (1975), Eisenbeis (1977), Scott (1978), Altman and Eisenbeis (1978), and Kohara and Ishikawa (1994). The limited success of the MDA methods has been greatly highlighted by these authors. Although several reasons were given, only four limitations are worth mentioning here:

- The MDA methods of analysis procedures assume that the variables used to describe members of the groups of companies being investigated are multivariate normally distributed (Alici and Valtchanov, 1994). This is known as the normality assumption. This assumption may not be valid especially when modelling the predictions of corporate failure where deviations from the normality assumption appear to be the rule rather than the exception. This implies that violations of the normality assumptions may bias the test of significance and estimated error rates.

- The validity of MDA has been sharply criticised because the validity of its results hinges on restrictive assumptions (Eisenbeis, 1977).

- The two principal ways for reducing dimensionality in discriminant analysis as suggested by Altman, 1968 are to eliminate (1) those variables or (2) those discriminant functions that do not contribute significantly to the overall ability to discriminate among groups. To date, the dimension reducing methods used have focused solely on the knowledge of the trade-offs involved between alternative reducing criteria. This can often be useful in business problems where it is often possible to generate a large number of variables which need to be pared down to some manageable size in a univariate analysis rather than multivariate. This re-affirms the point that the application of multivariate discriminant analysis to bankruptcy prediction is a misfit and impracticable.

- MDA methods of analysis procedures assume that the companies being investigated are discrete and identifiable. However, rhetoric appears in literature (Altman et. al., 1977) which violates this assumption. The extreme case occurs when an inherently essential variable is segmented and used as a basis to form groups. As a practical matter, the only time it really makes sense to classify companies into groups based upon the distribution of a particular variable is if natural breaks or discontinuities appear. For example, classifying firms into bankrupt and non-bankrupt. However, it is true to say that both groups can produce some identical characteristics

## 2.6 Non-Financial Indicators

So far, the explanatory variables (financial ratio indicators) have been discussed. Financial ratios are not the only variables which might explain corporate failure. However, the readings conducted by this study suggest that this particular aspect had been completely ignored in previous studies on corporate bankruptcy research. This study, for the first time, will now consider the significance of non-financial indicators in the modelling of corporate bankruptcy prediction.

Apart from financial ratios drawn from companies' financial statements, there are variables that can be examined in the context of corporate bankruptcy studies to see whether they help to identify perilous conditions of bankruptcy in the accounts of apparently currently operating companies. The explanatory variables (non-financial indicators) are of two types:

- Those which can be measured in ratio scale- i.e. using money values (such as UK Gross Domestic Product) or other proportionate measures (for example, Bank of England 'Interest Rates Policy').

- Those that involve a dichotomous ordinal scale- i.e. where 0 might indicate a Government known for extreme policies, 2 the ongoing economic situation in a country (for instance, gloomy economy). Although it is particular difficult to measure in terms of ordinal scale, and not all-statistical models can easily accommodate such indicators.

The distinction above is necessary since it explains which type of indicator to be applied in a particular situation and under what circumstances. In the former case, the criterion for their use seems to be that they can be measured with certain degree of objectivity; in the latter, measurement is usually based on observation and the personal intuition of the researcher. However, their effects on the survival of a business can be quite catastrophic. Both types can be forced upon any company conducting business in a particular economy (for instance, the UK) and may eventually mean the difference between success and failure.

Altman et. al., (1981) argue that the incidence of corporate failures appears to vary with the business cycle, invariably, the number of corporate collapses seems to rise during the period of recession. On a priori grounds (domain knowledge) it would therefore seem appropriate to include one or more such variables (macroeconomic) in any corporate failure identification model since these might be expected to improve its explanatory power.

A company vulnerability to bankruptcy is just as likely to be associated with the financial as well as the non-financial indicators. For this simple reason, the author considered using both type indicators to model the application designed by the study. The author thought that it is possible to achieve a high explanatory power in corporate failure model identification if both indicators are properly identified during the modelling process. The fact that particular industries are vulnerable at different stages in the economic cycle is easily appreciated by the author. For example, between 1979 and 1983 many companies suffered when there was a sharp rise in the Bank Rate announced by the Bank of England (Duffy, 1997). Similarly, in the late 1980s companies that were overdependent on bank borrowing to survive were hit when the 'Borrowing Rates' of the Bank of England rose unexpectedly (David et. al. (1997).

## 2.7 Summary

Deriving statistical models for the predictions of corporate bankruptcy was started with the use of univariate methods of analysis. This is the work of Beaver, (1966). The approach ignores interactions between variables and it concentrates narrowly on numbers drawn from the financial statements of failed and non-failed companies. However, these financial variables can in turn be generated by economic events, and the task of the financial analyst is therefore complicated by having to identify suitable benchmarks. Furthermore, also other problems can be encountered by the financial analyst when calculating financial ratios. In the circumstances, it is recommended to usually refer to information outside the companies' financial statements to build up a picture of a company's financial performance and current position.

Since univariate methods of analysis have limited use in predicting corporate failure, it was thought by numerous researchers that the MDA methods of analysis would do well. However, this is not the case of course. The MDA approach suffers from normality assumption which is a serious setback. Apart from this obvious weakness, the MDA methods of analysis provided no significant superiority over the univariate approach except to say that it is a popular procedure based upon selecting few more variables than the univariate approach which is based upon the use of a single variable.

It is clear that some non-financial indicators (as described earlier) can be referred to both in order to try to get early warning of financial distress and to establish the underlying economic causes of failure. Empirical evidence suggests that all these can be used as indicators to help discriminate between failing and non-failing companies.

Because business activities are conducted in an unusual stochastic and random environment, it is rather difficult to envisage how statistical approaches can perform very well in predicting corporate bankruptcies. However, they can do very well within the context of the samples used to derive the models. Statistical models will not have good generalisable capability because the properties of accounting numbers do not permit any models with few parameters to capture the irregularities in financial ratios due to the stochastic nature of financial ratios. Having said that, in developing a model of failure prediction, a wide range of cases should be included in order to capture ambiguity and randomness in the data. So far, literature on corporate failure prediction has failed to present a solid theoretical background where all symptoms could be detected. The author expects that the techniques that will be explained in chapter 3 may provide answers to the shortcomings of the univariate and multivariate discriminant analysis.

# CHAPTER 3

# NEURAL NETWORKS AND THEIR APPLICATIONS

## 3 Introduction

The previous chapter has described procedures used by numerous researchers to examine the characteristics of financially distressed companies and review the empirical evidence relating to their application. In particular, it was concerned with the use of univariate and multivariate discriminant analysis to model the application of corporate failure prediction. The statistical techniques described in the previous chapter serve to identify the underlying positive approach which might explain why it is so important to predict failing companies.

The main concern in bankruptcy studies is that many researchers have generally sought to rely on statistical techniques to develop corporate bankruptcy identification models. However, statistical techniques, particularly univariate and multivariate discriminant analysis are not appropriate because these techniques are valid only under certain restrictive assumptions, including the requirement for the discriminating variables to be jointly distributed according to a multivariate normal distribution. Should this not be the case, results obtained by the discriminant analysis procedure may be erroneous and impracticable (Wilson and Sharda, 1994; Eisenbeis, 1977; Toffleson and Joy, 1978). Another argument was advanced by Wood and Dasgupta (1995). The authors said that parametric models results hinge on certain restrictive assumptions such as log – normality or sample path continuity. It is commonly agreed that parametric models could only adjust to ad hoc procedures. It is therefore obvious that an alternative approach should be considered to tackle this important phenomenon.

Neural Networks represents a field of study within Artificial Intelligence area where researchers are studying a "biologically inspired" way of processing information. In order to introduce a general understanding of neural networks, particularly those aspects useful for the study, the biological basis of neural networks is presented.

## 3.1 Biological Basis of Neural Networks

Every day of our lives, each of us carries out thousands of tasks that require us to keep track of many things at once and to process and act upon these things instantaneously. Relatively simple actions, such as catching your usual train to go to work and dialling a telephone number involve many pieces of memory, learning, and physical co-ordination. The complexity of such "simple" tasks, which most of us do all the time without "thinking" about them, is underscored by the difficulty involved in teaching robots to perform them.

The human brain is composed of special cells called neurons. Estimates of the number of neurons in the human brain range from 80 to 100 billion (Grossberg, 1988), and more than a hundred kinds of neuron are known (Trippi and Turban, 1996). Neurons are divided into inter-connected groups called networks and they provide specialised functions (Nelson and Illingworth, 1994). Each group contains several thousand neurons that are highly interconnected with each other. Thus, the brain can be viewed as a collection of neural networks. The major component of biological neurons is shown in Figure 3.1 below.

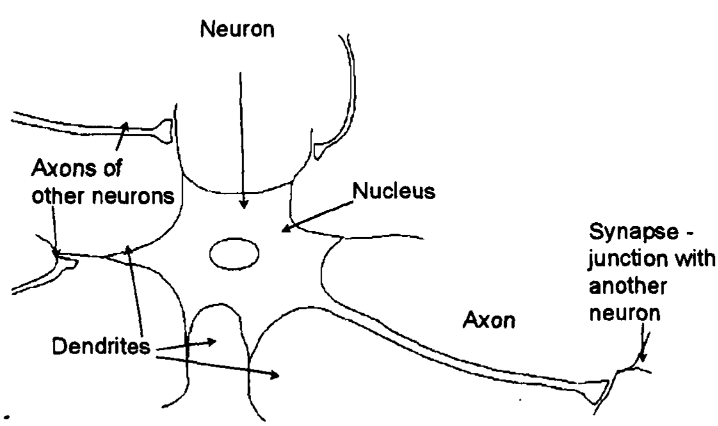



**Figure 3.1 The Neuron as a Biological Abstraction**

The major component of biological neurons and neural networks are compared in Table 3.1 below. This table shows the biological neurons and its neural networks processing derivatives.

| Facts about Neurons | |
|---|---|
| Biological | Artificial |
| Soma | Node |
| Dendrites | Input |
| Axon | Output |
| Synapse | Weight |
| Fast Speed | Slow Speed |
| Many Neurons (100 billion) | Few Neurons (100's) |

**Table 3.1 A biological Neuron versus Neural Networks**

According to Grossberg (1988), the output of the neuron corresponds to a signal sent out from a biological neuron over its axon. The axon of the biological neuron branches to the dendrites of other neurons, and impulses are transmitted over synapses. He said that a synapse is able to increase or decrease its strength, thus affecting the level of signal and causes excitation or inhibition of a subsequent neuron.

The neuron can be considered as a computing device since it carries out a simple threshold calculation. This is shown in Figure 3.2.

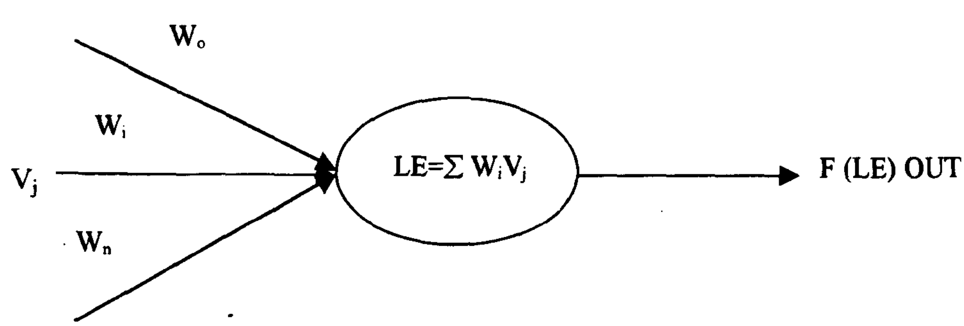



**Figure 3.2 The Neuron as a Computing Device**

A neuron is believed to carry out a simple threshold function. It collects signals at its synapses and sums them (Grossberg, 1988). If the combined signal strength exceeds a certain threshold the neuron sends out its own signal which is a transformation of the original input signal (Hecht-Nielsen, 1990). Consequently, the transformation between the total input signal and the output signal is determined by a nonlinear function. These transformation functions are known as hard limiters, sigmoids and pseudolinear functions (Grossberg, 1988). Hard limiter functions produce values in the range [0, 1], depending on whether the total input of a unit exceeds the threshold value. This type of function is commonly used in neural network learning because of its simplicity, which in a sense makes mathematical proofs relatively simple. Sigmoid functions are more complex, differentiable, and are widely used for many financial applications.

Neural Networks can easily be understood from the functional and structural perspectives. The functional perspective of neural networks is that they are arbitrary non-linear correlators. Correlators simply extract information from existing data, however, the correlations must exist generally in all data from the same source. At this point, two situations can occur. If the relationships discovered by a neural network in the data submitted to it hold true in the general data corpus, the neural network is said to generalise. On the hand, the neural network may simply "memorise" the training data and becomes very poor at generalising. A neural network model which simply memorises the training set is not useful and can occur only if the data sample submitted to the network is too small and the network discovers complex relationships which are only specific to the training data. Much of the art of making good neural networks is to do with ensuring effective generalisation capability.

The awareness of the computational properties of neural networks as a new modelling methodology provides an extra edge of freedom in deciding whether the use of this unique methodology is desirable for predicting corporate bankruptcy. A simple taxonomy would explain this point further. At the low level, we have a particular problem for which we have sufficient and precise understanding of the complexity of the system we are trying to model. For example, using the corporate bankruptcy phenomenon, the domain expert will use his experience to select those explanatory variables that have the predictive power in evaluating corporate financial performance. Consequently, for this particular problem, it is possible to specify the equations of the problem and subsequently select the algorithms to implement the required solution. This is the algorithmic modelling phase, which, in some sense are strict and strong with no free parameters. At the high level, numerous neural network architectures need to be constructed. Both inductive and deductive reasoning have important roles to play at the low and high levels.

Baestaens et. al. (1994) have noted that neural networks are data driven models generally built around non-linear activation functions (or non-linear transfer functions). It has further been noted in their study that neural networks are allowed to determine the non-parametric dynamics of a data set with minimal assumptions. These characteristics make neural networks suitable for the modelling the corporate bankruptcy phenomenon. The reason for this assertion is that neural networks are adaptive and can respond to structural changes in financial data of companies. Financial data is noisy and may contain errors, however, neural networks tend to be robust to the specification of errors that plague parametric models. Since neural networks are data driven, they therefore require substantial amounts of data to achieve a stable mapping of inputs onto outputs.

In this research, the multilayered feed forward neural network is used. A typical multilayered feedforward neural network is depicted in Figure 3.3 below.

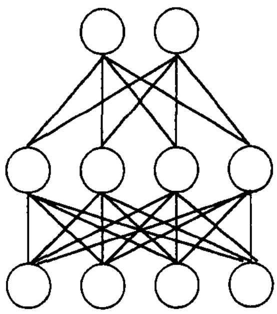



**Figure 3.3 An Example of the Feedforward Neural Network**

The three-layer neural network shown in figure 3.2 above has five important features. These important features are now described below.

1. The model comprises a number of 'processing elements' (or 'neurons') and 'connections' (or 'links'). The processing elements are organised in layers and can be constructed hierarchically. The bottom layer is the input layer, the middle layer is the hidden layer and the top layer is the output layer.

2. The models are generally constructed as 'feed-forward network'. Each of the processing element or neuron receives and combines 'input signals' from neurons in the preceding layer and transforms them into a single 'output signal'.

3. Each output signal is in turn sent from its processing element as an input signal to other processing elements and possibly back to itself.

4. The signals are passed around the network via 'weighted interconnections' (or 'synapses') between the processing elements. Each connection carries an associated weight with it. The weight is numerical in nature. The weight shows the influence of an input neuron on an output neuron, with positive weights indicating reinforcement of a relationship and negative weights a weakening.

5. Network knowledge is stored on the way in which the processing elements are connected with each other in order to transfer signals and on the nature and strength of the connections. Computer algorithms establish a 'training network' to detect relationships between 'input data' and 'output data' so that situations can be classified correctly.

Neural networks have assumed a promising role in commercial applications (Croall and Mason, 1992). For example, Chase Manhattan Bank in New York developed one of the largest and most successful neural network applications in assessing the creditworthiness of their corporate clients (Nelson and Illingworth, 1994). Barclays Bank in England developed CREDEX (a neural network application) to assess the creditworthiness of their corporate clients (Nelson and Illingworth, 1994). It is believed that the next decade will see neural networks assuming a prominent role in commercial applications development. Neural Network research is a continuing process and as new developments are produced, their importance will become prevalent in our society.

The rest of the chapter is organised as follows. Section 3.2 presents the back-propagation algorithm. The development cycle of the backpropagation algorithm is presented in section 3.3. The reasons for suggesting the use of neural networks for predicting corporate failure are presented in section 3.4. Previous works on the use of neural networks in predicting corporate bankruptcies are discussed in section 3.5. Section 3.6 provides an overall summary and conclusions.

## 3.2 The Backpropagation Algorithm

### 3.2.1 Introduction

The back-propagation network (BPN), which is also sometimes referred to as a multilayer perceptron (MLP), is currently the most general purpose, commonly used neural network paradigm (Taylor and Lisboa, 1997). Rumelhart et. al., (1986) argue that the BPN achieves its generality because of the *gradient-descent* technique used to train the network.

According to Rumelhart et. al. *gradient descent* is analogous to an error- minimisation process. *Error minimisation*, as its term implies, is an attempt to fit a closed-form solution to a set of empirical data points, such that the solution deviates from the exact value by a minimum amount.

The BPN learns to generate a mapping from the input to the output pattern space by minimising the error between the actual output produced by the network and the desired output across a set of pattern exemplars. The learning process begins with the presentation of an input pattern to the BPN. That input pattern is propagated through the entire network, until an output is produced. The BPN then makes use of what is called the *generalised delta rule* to determine the error for the current pattern contributed by every unit in the network. Each unit in the BPN modifies its input connection weights slightly in a direction that reduces its error signal, and the process is repeated for the next pattern. However, learning problems can occur particularly when the BPN is required to map a well-defined set of input units into a well-defined set of output units (Baestaens, et. al., 1994).

Rumelhart et. al., (1986) solved this mapping problem by introducing methods for training hidden units. The work of Rumelhart et. al., is looked in more detail in Chapter 6. However, a brief explanation would suffice here for now. Rumelhart et. al., provided the role that the hidden layer plays when the network is learning. In most cases, the hidden layer is learning an internal representation of the input patterns that will enable it to perform a non-linear mapping from the input space to the output space. Other aspects of the BPN are now presented.

### 3.2.2 Neurons

The neurons known as the processing elements of the BPN. The BPN processing elements is depicted in figure 3.4 below.

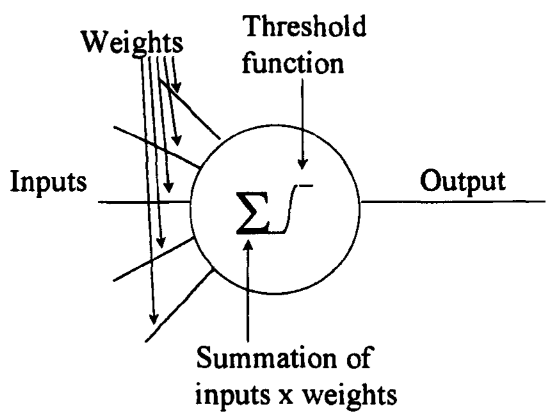



**Figure 3.4 The Processing Elements of the BPN**

Each neuron receives input data, processes it, and delivers a single output. This process is shown in Fig. 3.4 above. The input can be raw data, or output of other processing elements. An artificial neuron is a simple operator that computes a weighted sum V of its input units $x_i$.

$$V=\sum_{i=1}^{N} W_i\, x_i = \vec{W}.\vec{X}$$

where N is the dimension of the input space.

The sum above is then compared to a threshold $W_O$ and followed by a non-linear activation function $f$, and this can be described as the decision function.

### 3.2.2 Input units

Each input unit corresponds to a single attribute of a pattern or any other data; such as the output from another network. The network can be designed to accept sets of input values that are either binary-value or continuously valued. For example, if the problem is to decide whether or not to approve a bank loan, an attribute can be credit history, marital status, income level and monthly outgoing and so on. Neural networks would only accept numerical equivalent. They do not recognise symbolic data. So, therefore, symbolic data must be processed to a numerical equivalent before neural networks can interpret it. Neurons like to see data in a particular input range to be effective. Presenting data that varies from £500,000 to £1,000,000 (as the companies financial statements have over the years) will not be useful, since the middle layer of neurons have a sigmoid activation function that squashes large inputs to either −1 to 1 or 0 to 1. A typical non-linear squashing function is:

$$\Upsilon_T = \frac{1}{1+e^{-y}}$$

where $\Upsilon_T$ is the transformed value of $\Upsilon$

### 3.2.4 Output

The output of the network is the solution to the problem. For example, in a typical application of neural network to accept or reject a loan application, the network may have one output unit to "accept" or "reject". The network will produce numerical values and it is up to the developer to interpret the neurons output accordingly. The network values acceptance depends on the scale of the problem. It is at this stage that a decision will be made whether or not to accept the network's output. If it is accepted, the network is recognised; however, if it were not accepted, the network would have to be trained further or terminated as a failure (Hammerstrom, 1993).

### 3.2.5 Hidden Layers

In a typical three layer network (see Figure 3.2), the middle layer is known as the hidden layer and the processing elements in the hidden layer is known as hidden units or nodes. They are called "hidden" layers because they are not visible from the outside world. Hidden layers are feature extractors. The hidden layer of units acts as feature detectors, activating only in response to certain conditions at the output of the input layer. The required number of hidden layers and the number of processing elements in each hidden layer depends on the scale of the problem. The size must therefore be carefully selected to match the complication of the problem (Humpert, 1989). Most problems can be solved with a single hidden layer (Hush and Salas, 1988). However, Hirose et. al., (1991) point out that if more than one hidden layer is used, subsequent layers must be connected to all prior layers. The number of training examples can determine the theoretical upper bound for the number of hidden layers.

### 3.2.6 Weights

The weights in a neural network express the relative strengths of various connections that transfer data from layer to layer. The weights express the relative importance of each input to a processing element. Weights are crucial to the network because they are the means by which the network is repeatedly adjusted to produce desired outputs and thereby allow the network to learn (Nelson and Illingworth, 1994). When a network is first set up, the weights should be given some initial values (e.g. zero) from which the learning process may begin. The reason for this is to avoid imposing any prejudices about the application to the network.

### 3.2.7 Summation Function

The summation function finds the weighted average of all the input elements to each processing element. A typical, simple summation function will multiply each input values ($X_S$) by the weights ($W_S$) and totals them together for a weighted sum, $\Upsilon$. For $N$ inputs $i$ into one processing element $j$, we have:

$$\Upsilon_j = \sum_{j}^{n} x_i \; w_{ij}$$

The neurons (hidden units) in a neural network thus have very simple processing requirements. The neurons in a typical network monitors all incoming signals from other hidden units, compute the weighted sum, and then determine a corresponding signal to send to other hidden units (Medsker and Liebowitz, 1994).

### 3.2.8 Learning

Learning is the process by which the network adjusts its weights in order to produce the correct output. The set of weights values for a given network represents its understanding of the possible inputs.

In Hebbian learning, weights between learning nodes are adjusted so that each weight better represents the relationship between the nodes. Consequently, nodes which tend to be positive or negative at the same time will have strong positive weights while those which tend to be opposite will have strong negative weights. Nodes, which are uncorrelated, will have weights near zero.

The general formula for Hebbian learning is

$$\Delta w_{ij} = n * input_i * input_j$$

where:

| | |
|---|---|
| n | is the learning rate (usually adjusted in the Global Learning Schedule) |
| $input_i$ | is the external input to node i |
| $input_j$ | is the external input to node j |

The more recent learning rule is the Rumelhart and McClelland, (1986) Delta Rule. In general, the Delta Rule outperforms the Hebbian Rule (Werbos, 1988). For each learning cycle, the pattern is propagated through the network *learning parameters* in multiplication after which learning occurs. Weights are updated according to the following rule:

$$\Delta w_{ij} = n * d_i * a_j$$

where

| | |
|---|---|
| n | is the learning rate |
| $a_j$ | is the activation of the source code |
| $d_I$ | is the error of the source code |

The above learning law is useful when training the BPN. At this juncture, two types of network are discussed briefly.

There are two types of neural networks, the supervised and unsupervised networks. In supervised networks, the algorithm learns how to respond to patterns of data presented to it. Supervised networks require the help of the teacher to learn properly. In unsupervised networks, the network learns categories on input patterns presented to it without the help of a teacher. There is no knowledge supplied about what classifications are correct, and those that the network derives may or may not be meaningful to the person training the network. An important function of learning is that the network evaluates the inputs presented to it and produces an output in response to it.

In this study, the supervised network will be used since domain expert knowledge of the author will be supplied to the network. Supervised networks have been popularly used for classification problems and are particularly suitable for the corporate bankruptcy problem (Odom and Sharda, 1990; Alici, 1995).

## 3.3 Neural Networks Modelling Cycle

The development cycle of neural network applications can be described in a way that is similar to any other system design; however, some steps are unique to neural network application development.

Nelson and Illingworth, (1994) suggest four phases:

- the concept phase
- the design phase
- the implementation phase
- the maintenance phase

The above process assumes that other phases of development, such as information requirements and feasibility analysis for the project, have been successfully completed. What follows is the detailed modelling cycle.

### 3.3.1 The Concept Phase

According the Anderson and Rosenfield (1988), this phase plans the approach to building the application. In addition to traditional feasibility-assessment activities, the concept phase validates the proposed application and selects neural paradigms that may be suitable for meeting specific requirements. In the concept phase, the specific application is selected, the problem is bounded and scoped, and the basic functionality of the system is determined. The principal components of this phase are shown in Fig. 3.4. Successful neural network applications all have common characteristics, including:

- application area is data intensive
- application area involves multiple interacting parameters
- problem area is rich in historical data or examples
- data incomplete and contains errors and distractions
- function to determine solution is unknown

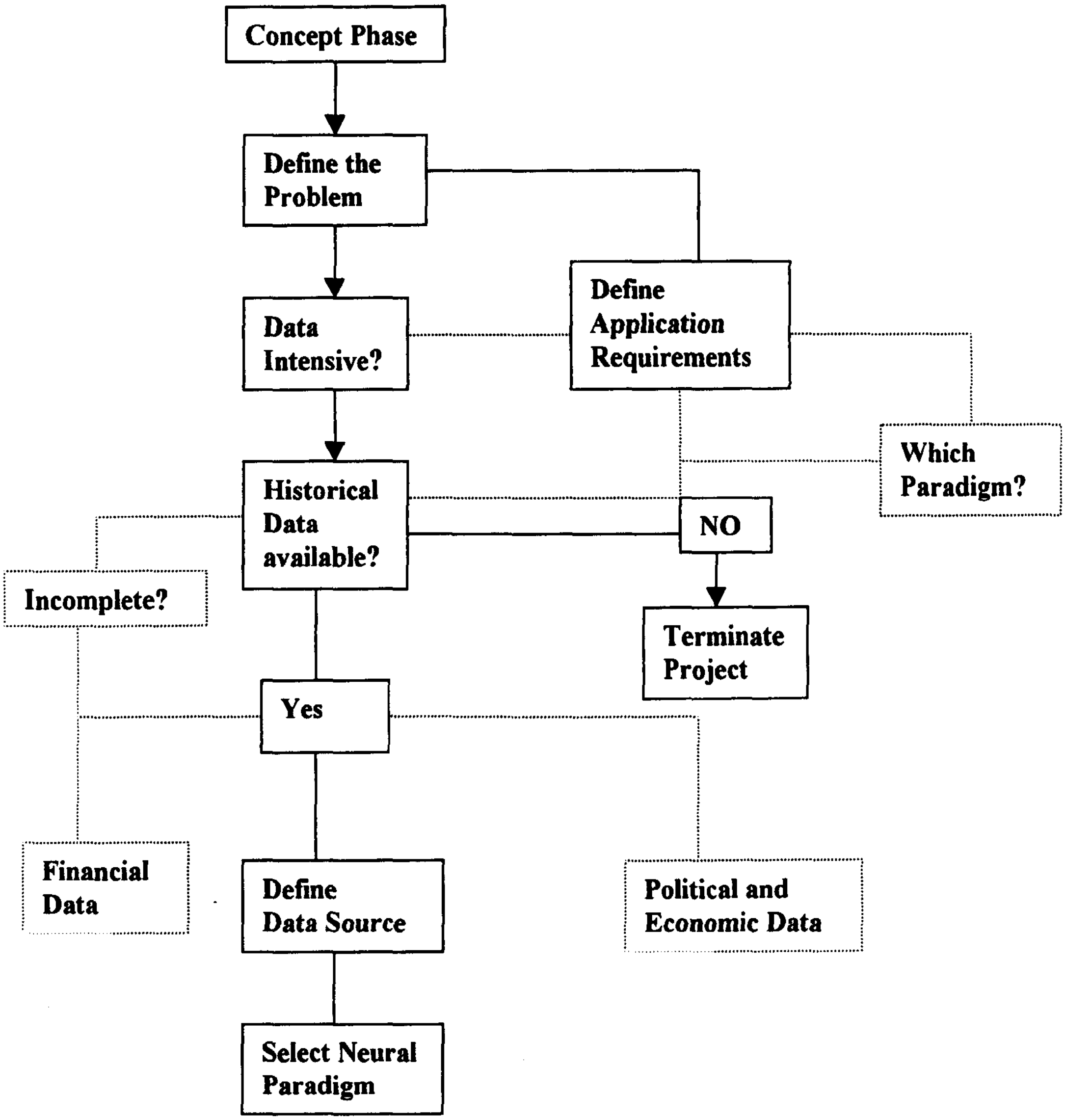


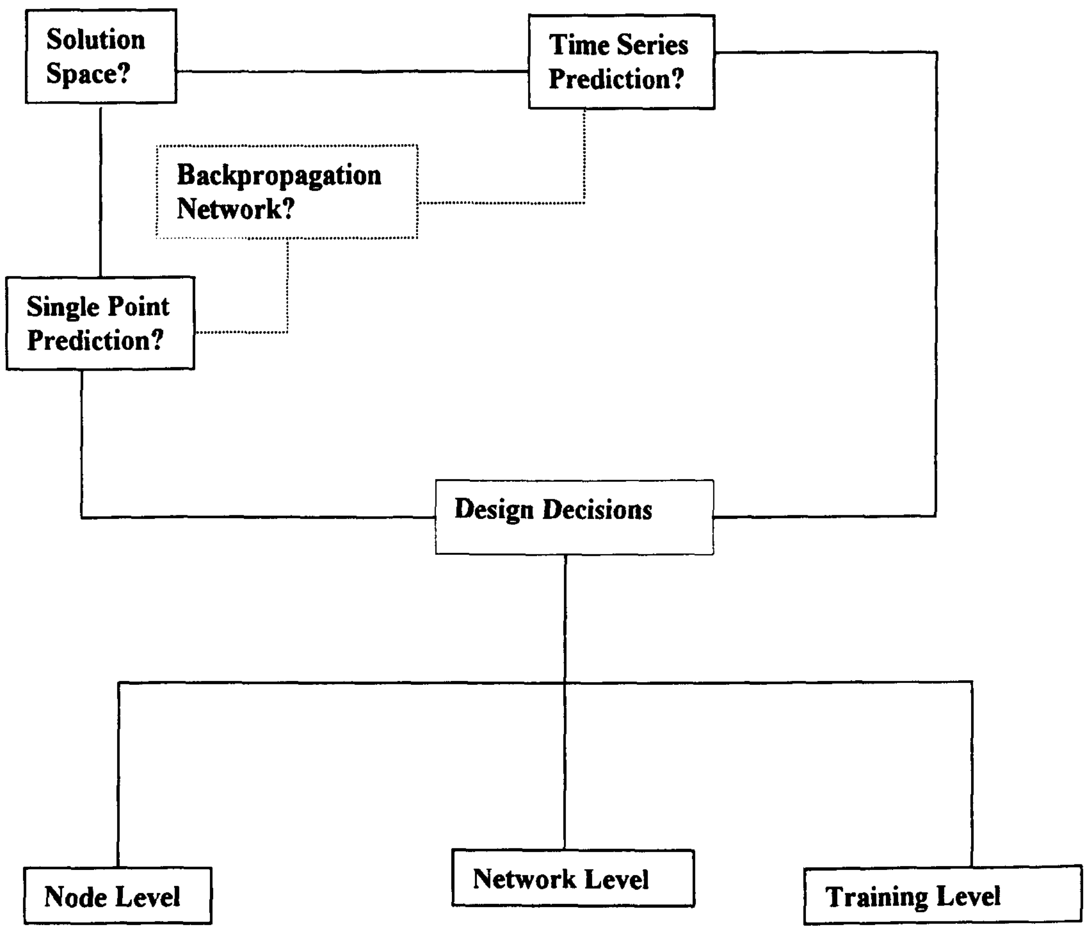

**Fig. 3.4: Neural Network Concept Phase**

The latter stage of this phase is to select an initial set of neural paradigms. As mentioned earlier, the selection should be based on the comparison of application requirements to neural paradigm capabilities. For completeness, of particular interest are size, required output type, method of training and time constraints. Existing successful applications can be consulted to confirm choice of paradigm and method of training.

### 3.3.2 The Design Stage

Neural network is a system that needs to be designed at different levels: node, architecture selection, and training (Anderson and Rosenfield 1988). These levels and decision considerations are shown in Figure 3.5 below.

**Figure 3.6 Major Decisions in Training Neural Networks**




| Node Level | Network Level | Training Level |
|---|---|---|
| 1. Input type | 1. Number of layers? | 1. Learning Algorithm |
| 2. Transfer Function | 2. Number of nodes? | 2. Halting Conditions |
| 3. Means of combination | 3. Size of Hidden layers? | 3. Confirm Errors |
| 4. Check Network Biases | 4. Output nodes? | 4. Test Network |
| 5. Layer Parameters | 5. Connectivity? | 5. Validate Network |

It follows from the above that the types of processing elements, the size and connectivity of the network layers, and learning algorithm should all be determined at the design stage (Nelson and Illingworth, 1994). Neural networks are usually described in terms of their connectivity, architecture type, and weights. The architecture selected depends on the nature of problem and the solution space. At the node level, the designer needs to address type of inputs, connectivity to the hidden layers and appropriate transfer function. The required output type will determine the number of output nodes.

### 3.3.3 The Implementation Phase

This phase involves the actual construction of the neural network, data loading and commencement of training of the network. The procedure is shown in Fig. 3.6.

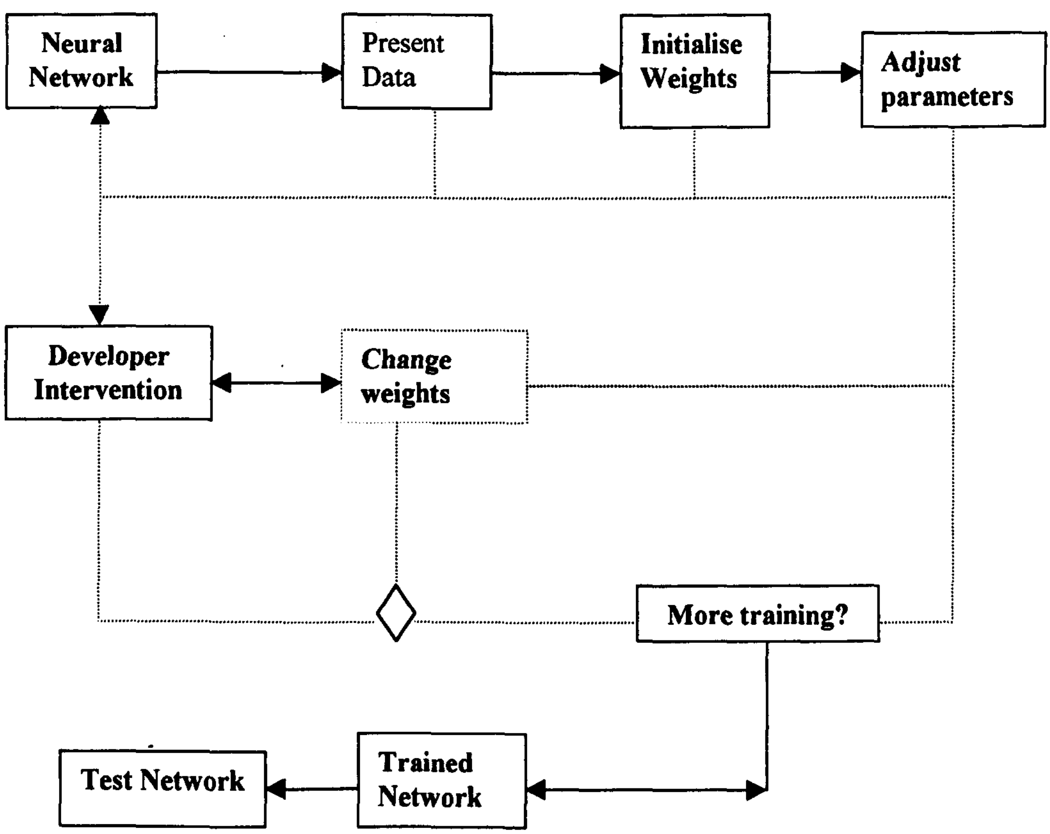



Figure 3.7 Neural Network Implementation Stage

### 3.3.4 Network Maintenance

The sole aim of the maintenance stage is to evaluate periodically the system's performance and to modify it as when necessary (Hinton, 1987; Caudill and Butler, 1990). The system should be constantly updated in order to promote efficiency and applicability. The compatibility of the system when integrating with other systems as part of hybrid solutions should be weighed appropriately.

In the next section, the author explains why neural networks should be used for the corporate bankruptcy prediction problem.

## 3.4 Why Use Neural Networks?

### 3.4.1 Introduction

Corporate financial analysts have traditionally relied on models, which relies on the assumptions of partial equilibrium. Such models have been very useful in expanding our understanding of corporate failure modelling. However, many financial anomalies have remained unexplainable. Predicting the financial status of the particular company is often complex and intractable (Odom and Sharda, 1990). The prevailing wisdom amongst financial analysts is that corporate bankruptcy not due to external influences are dominated by noise and flagrant abuse of internal controls instituted by management and can be modelled by stochastic processes. Consequently, we try to understand the nature of noise and develop application tools for predicting corporate bankruptcy by taking into consideration both internal and external influences.

Many reasons explain why neural network approach may produce results superior to regression-based approaches for analysis of financial data. What follows are some of the main arguments that could reasonably be advanced in support of neural networks for modelling the corporate bankruptcy phenomenon.

Predicting corporate bankruptcies is well known to be very difficult because of the necessity of capturing a complete understanding of the problem domain. Many statistical tools have been developed to assist financial analysts in this goal. Although useful, these tools often fall short in handling difficult situations such as incomplete data sets or grey areas in which the expert may not thoroughly understand the process or study. Neural networks are able to recognise patterns in accounts of companies even when the data is noisy, ambiguous, distorted, or variable (Coats and Fant, 1992). Neural networks continue to perform well with missing or incomplete data, a task most difficult with regression based models (McFadden, 1976).

A neural network is capable of discovering data relationships, whereas regression model building presumes knowledge of the underlying relationships (Eisenbeis, 1977). This important characteristic is essential in modelling the corporate bankruptcy phenomenon because neural networks generated outputs are not sensitive to monitor variations in the input patterns. This robustness can be taken as an important feature when performing financial analysis of corporate accounts since yearly variations in companies' activities usually occur (Altman et. al., 1994).

It has been argued by Baestaens et. al., (1994) that the primary advantage of neural networks over classical regression analysis is that learning algorithms have more general functional forms than do other well-developed statistical methods. Neural networks do not depend on linear superposition and orthogonal functions, which linear statistical regression approaches must use (Eisenbeis, 1977; Zavgren, 1983). Consequently, the function approximations that arise from properly applied neural networks are usually better than those provided by regression techniques (Odom and Sharda, 1990). This difference is particularly important in high-dimensional spaces where many of the highly regarded statistical techniques often fail to produce an appropriate approximation (Eisenbeis, 1977).

Nasir et. al., (1999) argue that providing a large number of input parameters to a neural network does not pose a model structure problem as in regression. However, if the data turns out to be unimportant in solving the problem, the network will learn to ignore it by assigning near-zero values to weight the data. Thus, the network may provide an enhanced capability to analyse financial statements composed of numerous, linearly dependent accounts and aggregates.

Forecasting corporate failure follows two distinct approaches. Having the exact knowledge underlying the phenomenon. When this knowledge can be expressed in terms of precise equations, which in principle can be solved, then neural networks would not produce a better alternative than the classical approaches. It is because explicit knowledge of the domain governing the behaviour of companies are not readily available because of parameter instability that makes neural networks suitable for this kind of problem. The discovery of strong regularities in observations of financial parameters also makes a special case. If strong regularities can be easily observed in corporate accounts, then neural networks would not produce better results because the regularities can be measured by simple rule of thumb. However, it is because regularities are not always evident in financial parameters, and are often masked by noise, which makes neural networks suitable for this kind of problem.

Non-linear modelling techniques are the subject of increasing interest from practitioners in quantitative financial business forecasting with neural networks assuming a prominent role. Neural networks are being applied to a number of financial applications such as detecting credit card fraud, mortgage lending advisor and recognising signatures on bank cheques (Nelson and Illingworth, 1994). However, one major disadvantage of neural networks is that they have been perceived as "black-boxes" which are not capable of explaining how to reach an outcome. Naturally, the acceptability of any technology including neural networks to corporate financial analysts will clearly depend upon the technology's ability to provide an explicit representation of the relationship that they estimate. Therefore, it is important to formulate neural computation as non-parametric regression systems, which enables us to extract explicit non-linear models (Weigend and Gershenfeld, 1993).

The inductive nature of neural networks gives them the ability to bypass the step of theory formulation and to infer complex non-linear relationships between corporate bankruptcy and its determinants (Blinks and Allinson, 1991). Having said that, there are strong reasons to believe that complex non-linear processes determine the relationships between corporate bankruptcy and their determinants. Neural networks provide a suitable methodology for modelling this type of relationship (Altman, 1993).

Financial analysts often find themselves overwhelmed with vast amounts of financial data information (Nasir et. al., 2000). Most of this information or data is numeric, often incomplete, and very noisy. Typically, the analyst processes a large subset of financial data both quantitative and qualitative from several sources extracting relevant information to make business decisions. These decisions frequently rely on the integration of statistical measures that attempt to compress much of the data and qualitative depictions such as graphs and bar charts and other pertinent information such as their own recommendations. Although analysts can factor in such relationships in the analysis, they may not be able to analyse and combine disparate information that can potentially affect their own prediction. Neural networks, in general, are very adept at managing large amounts of numeric information and they perform very well in this prospect than statistical regression (Coakley and Brown, 1991).

Neural networks have become popular for tackling complex financial problems ranging from prediction of assets prices (Zapranis, 1992), index of stock and shares, currency exchange rate forecasting (Refenes et. al., 1993), and the predictions of corporate bankruptcy (Odom and Sharda, 1990; Nasir et. al., 1999). Such problems can be thought of as involving the prediction of the value of one variable based on several other variables that can effect it. In the corporate prediction domain, proper neural network design is critical for generating good forecasts. It has been suggested in the literature (Refenes et. al., 1993) that the more task-specific the neural network, the more effective it is. For instance, constructing a neural network to forecast corporate bankruptcy may be more effective than forecasting both the trend of financial variables and its amplitude because of noise and possible randomness inherent in financial data.

Company directors almost certainly are very economical with disclosure of financial information. Two reasons can be identified. Company directors are allowed to depart from the standard accounting practice if to do so would show a true and fair view of their financial affairs. The other reason is that they conceal information from their competitors in order not to create a predator and victim situation. Disclosure of too much information about the strengths and weaknesses of a company would almost certainly lead to take over raids from rich competitor large companies. In this case, the expert should therefore deduce economically produced information by reconciling company activities from the information disclosed in annual financial statements. Statistical regression cannot be used to deal with incomplete, variable, or noisy data; data information must exist for regression based models to work (Eisenbeis, 1977). One of the most important results in neural computation research is the proof that neural networks are universal approximators (Refenes and Azema-Barac, 1993). In other words, given a sufficiently large number of free parameters the learning procedure is *guaranteed* to find a mapping between any set of independent and dependent variables (Hecht-Nielsen, 1990). This is a very important result as it implies that neural networks can tackle the widest possible range problems including the corporate bankruptcy prediction. In the next section, the author presents applications of neural networks.

## 3.5 Applications of Neural Networks

### 3.5.1 Introduction

This section will present previous works on neural networks for predicting corporate bankruptcies. A vast amount of literature has emerged concerning the development of the appropriate neural network architecture for predicting corporate bankruptcies. The current tendency in failure prediction emphasises the use of simple models derived from the financial data one year prior to failure. Neural networks are commonly used to learn and predict time series, but most of the approaches aim at only point-prediction (Husmeir and Taylor, 1977). Consequently, further information about the possible distribution is lost, which is a serious draw back especially in the case of multimodality.

Suppose that we want to predict the financial status of some companies in 1996. We further assume that all detailed financial and descriptive information about the companies is available. In order to predict 1996 for example, we obtain data from 1992 through 1995. Using the next time step $x(t+1)$ for example means that we have to time shift 1992 through 1993; 1993 through 1994; and 1994 through 1995 to predict the financial status in 1996. The possible pitfalls awaiting the unsuspecting financial analyst is that failure hypothesis do not follow a *random* walk but a *chaotic* one. Therefore, in order to produce a valid model, the entire information representing the period under study involving the company activities must be captured in some sort (Hoptroff, 1993). Furthermore, numerous researchers, such as Waibel (1989); Refenes et. al., 1993; Hoptroff, 1993; and Jang et.al., (1991), have shown how the temporal dimension can be transposed into vector by taking a moving window over the last $n$ elements in a series. Using a feedforward neural network with $n$ inputs i.e. one for each time step up to $t$ and one output unit representing the value of the series $t+1$, we can learn to perform one step ahead prediction. Refenes (1992) suggested that it is possible to extend the predictions to several steps ahead by simply increasing the output window size and feeding the single output back to the end of the input window. However, Swinger, (1996) argue that this can produce exponentially growing errors.

Weigend and Gershenfeld (1993) trained a neural network to predict Swiss Franc exchange rate values one hour ahead. Taking the actual value ($t+1$), rather than the predicted value, as input to their network in order to predict the next step. It was reported that the network's result was overwhelming and superior. However, a closer inspection of their results shows that the network is simply predicting that the price level one-hour from now will be the same as it is now. A common quoted hypothesis reported by Refenes (1992) is that such a model is actually optimal.

Most of the observed time series do not satisfy the assumption of stationarity on which single point predictions rely. There is clearly a common assumption of the changing nature of business activities over time, which should be captured in modelling. Having said that, financial data series are often contaminated by noise from unknown sources and suffer from high-level measurement errors. This combination makes single point prediction unworkable in corporate failure modelling. The author will now present previous works in section 3.5.2 below.

### 3.5.2 Previous Research

Multilayered feedforward neural networks have been applied to many problem domains; however, this section will only consider previous works relevant to corporate bankruptcy modelling.

Among the first neural network failure studies was that of Odom and Sharda (1990). They adopted the work of Altman (1968) by employing the same number of financial ratios as described in Chapter 2. The study selected a sample of 65 failed companies and 64 non-failed US companies. The training set comprised 38 failed and 36 non-failed companies, the reminder being used as validation sample. A three-layer neural network was created with five hidden nodes. Convergence was achieved after 24 hours and 191,400 iterations. The neural network correctly identified all the failed and non-failed companies in the training sample, compared to a successful classification rate of 86% for a benchmark discriminant model. Both models were then tested on a hold out sample using prior probability of failure estimates of 50:50, 20:80 and 10:90. The neural network model correctly classified bankrupt companies in 78% or more occasions under all three-probability priors. However, for the non-failed companies, the correct classification is 79% for the network and 89% for the discriminant model.

Fletcher and Gross (1993) used backpropagation neural network to identify corporate bankruptcies from a sample of 18 matched pairs of companies. Employing three accounting ratios as the explanatory variables, they investigated the impact on the performance of their neural network models of the number of neurons in the hidden layer. The results shows that models with between 3 and 7 hidden nodes were better able to discriminate than comparable to logit models. However, the 82% correct prediction rate reported that was claimed achieved without adjusting for sampling bias, which suggests that none of the models would be very helpful in practice anyway.

Coats and Fant (1993) identify 94 manufacturing companies that are known to be bankrupt over the period 1970-1989. Against these they used 188 non-failed listed companies, almost half of which were not in the manufacturing sector. The training and test sets comprised 47 failed and 94 non-failed companies. As in Odom and

Sharda's study, the variables in the training set data were five financial ratios used in the Altman's 1968 discriminant study. The authors claimed the model achieved 80% classification after 1400 training cycles.

Wilson and Sharda (1994) used a training sample of 100 companies, which covers both bankrupt and non-bankrupt companies. The model was derived from one year prior to failure data. The authors used the same number of financial ratios (input variables) as the Altman (1968) study. The variables selected were five. The training algorithm used was backpropagation with one hidden and output layer. It was claimed in this paper that the network model was able to obtain a 100% classification of the training set and when submitting the test set, the network model achieved 73% accuracy in both cases.

Tam (1991) study developed a backpropagation model to identify bankrupt companies. This was constructed on a sample of 59 failed matched with 59 non-failed companies. The financial ratios selected were based on Altman's 1968 study. However, the misclassification errors were much higher than that reported by Altman.

Salchenbeger et. al., (1992) applied the neural network procedure to discriminate between 100 US companies which failed between 1986-1987 and a similar number of non-failed matched pairs. Applying five financial ratios, the neural network model consistently outperformed the Altman's 1968 model. Moreover, when testing against a situation where the proportion of non-failed companies to failed was more realistic, the neural network still performed tolerably well, although misclassification error for failing companies were much higher.

Wilson et. al., (1995) bankruptcy study cover a sample of 112 companies. These comprising 40 failed, 32 distressed, and 40 non-failed companies. A total number of 18 explanatory financial variables were selected for the experiment. The topology of the network comprised an input layer, hidden layer, and an output layer. Between 30-40 epochs were used before convergence was achieved after 100,000 training iterations. The model did extremely well when tested on the training sample but far less well when tested on the hold out sample. The misclassification error was far higher with respect to failed companies.

In a more recent study, Alici (1995) data set covers two main groups, the failed and healthy firms. The selections of 46 failed companies were matched with 46 healthy companies. As for the external ability of the derived models, 310 failed and 280 non-failed company cases were randomly taken from the MicroEXTAT data base covering all industries and hold out samples were conducted over five years for already failed companies between 1987-1992. He selected 28 financial variables by employing PCA and profile analysis to characterise those variables. He trained his network by using the Self-Organising Feature Maps (SOM) as a benchmark against his PCA model. A "skeletonisation" procedure was employed in order to establish the number of financial variables and optimum network structure. The prediction results from the model achieved 68% accuracy. It was also claimed that SOM could be used to group financial ratios before input into neural networks.

The rationale for numerous neural network approaches so far indicates that small training data samples are introduced and that the backpropagation algorithm is popularly used. The author now presents an alternative approach for dealing with the corporate bankruptcy phenomenon.

### 3.6 Summary and Conclusions

A number of neural network models have been developed in the industrialised countries of the world. These models have been developed to see how well they discriminate between bankrupt and non-bankrupt companies, and the performance of these models has been reported in a number of papers. The reason for the growing interest in neural networks is that academics seem to be moving toward the elimination of discriminant analysis as an analytical technique in assessing the performance of companies. Neural networks have the advantage over statistically derived models since they capture far more information in difficult and complex circumstances even though there may be noise and distractions in the financial data submitted to neural networks (Silva and Amelda, 1990).

However, the current tendency in using neural networks to prediction corporate failure emphasises the use of simple models derived from the financial data one year prior to failure. Moreover, most models used in company failure prediction summarise information contained in a company's financial statements, by selecting a limited number of financial ratios to assess a company's financial status and representing them as input units to neural networks. The properties of accounting numbers do not permit any models with few parameters to capture irregularities in financial data due to the stochastic nature of financial ratios.

The common approach is that neural networks are trained to predict the next time step $x(t+1)$ as a function of $m$ previous time steps. When the time series is huge and noisy, (as always the case with financial statements data) single point-prediction themselves are not very meaningful unless at least their confidence intervals can be predicted as well. Consequently, further information about the distribution is lost. This is a serious draw back especially in the case of multimodality, where the conditional mean alone turns out to be a rather insufficient or even misleading quantity. Nonetheless, the possible pitfalls awaiting the unsuspecting financial analyst is that failure hypothesis do not follow a random walk but a chaotic one. Therefore, the only satisfactory approach in general case is to predict the whole time series (Box and Jenkins, 1970; Hoptroff, 1993; Bishop, 1995).

Most of the observed time series do not satisfy the assumption of stationarity on which single point predictions rely. There is clearly a common assumption of the changing nature of business activities over time which should be captured in financial modelling. Financial data series are often contaminated by noise from unknown sources and suffer from high-level measurement errors. This combination makes single point prediction quite unreliable in corporate failure modelling.

In the next chapter, the author will present data processing for neural network. The pre-processing of data for neural networks is clearly an important one since it relates mainly to the problem under investigation by the author. It is perhaps important to state here that a well-processed data would ultimately produce a good model of neural networks since neural networks are data driven. What has to be remembered always when modelling neural networks, is that the particular neural network is as good as the data used to train it.

# CHAPTER 4

# PREPARING THE DATA

## 4.1 Introduction

The previous chapter reviewed and discussed neural networks and their applications. This chapter discusses data pre-processing for neural network inputs. Some aspects of the importance of the characteristics of the data in developing neural network applications have become apparent in the previous chapter. The financial statements of companies selected for this investigation had been prepared under currently accepted reporting standards as pronounced by the Accounting Standards Board. The study had employed the currently accepted form for analysing companies' financial statements in computing the so-called 'financial ratios' as prescribed by the United Kingdom Generally Accepted Accounting Practice (UKGAAP). The study collected real data from The London Stock Exchange, Jordans Financial Database of major British public and private companies, and the Bank of England.

The complexity of the problem at hand, coupled with the human factors of interacting and understanding the decision-making process of collecting the most suitable data, combine to make the task one that requires the use of considerable skills to process the available data in the manner suitable for neural network input. The collection of non-numerical factors such as political and economic events makes the problem even more complex and rigorous. Perhaps, it could be argued from the onset to state that the reasons for collecting non-numerical factors is that too much reliance cannot be placed on financial ratios on their own in modelling application of corporate failure. Having said that, non-numerical factors are 'independent predictive' variables that can explain a significant part of the variability of the dependent variable. An independent variable has no predictive power when considered alone, but, when combined with other dependent variables, can lead to better prediction.

The need to collect information outside the balance sheet makes the problem of data collection even more problematic and daunting. Relying on the financial statements alone can be less meaningful since information outside the realms of the balance sheets can lead to better explanatory power in identifying impending bankruptcies. This particular aspect in the modelling process created a number of further difficulties in an attempt to gather 'sufficient' data for this investigation. What is regarded as 'sufficient' data in the author's opinion can be stated as follows:

- collect all the financial statements of all major British public and private companies
- collect all the possible economic and political data
- gather information 'outside the balance sheets' from quality financial newspapers

The considerable difficulties in collecting the appropriate data for this investigation cannot be overemphasised. Perhaps the most important decision to take when modelling data for neural inputs is choosing the contents and sources of data for the model. Getting the most suitable data is often difficult because of the costs and legal implications involved in releasing financial data of registered companies. It is very expensive to get the most suitable data from a recognised authority (e.g. The London Stock Exchange) since a lot of human resources must be put into making sure that the data is complete and reliable. Data in the public domain are often unreliable because companies publishing their annual statements would almost certainly be economical with the most relevant information in order to avoid a take over raid from competitor large companies or on the other hand to distract the attention of the concerned corporate lending banker. As a result, the first step in the data selection process is always research. As already stated earlier, because of the logical nature of the data sought and its difficulties, some time was spent interviewing specialists in the field of expertise; this was done in order to provide further insight into the underlying process of identifying the most appropriate data sources.

The key to the success of this project was due the elaborate time spent in understanding what kind of information is relevant, seeking specialist advices from known experts in the domain area, and employing domain expert knowledge in collecting the appropriate and sufficient data that would allow this investigation to be conducted. It is from this premise that a number of issues have been addressed:

- Can a large dataset be obtained that are as complete as possible?
- What are financial variables?
- What are non-financial variables?
- What financial variables can be used to access the desired information?
- Can other variables (e.g. economic and political factors) or other relationships capture the same information indirectly?
- Are the variables always used or are they used only in special cases? What are those cases?
- Are the variables selected are as complete as possible?
- Are the variables selected significant enough to capture the underlying characteristics in financial data and non-financial data?
- Are the variables significance enhanced by additional data?
- What is information outside the balance sheet?
- How do we collect information outside the balance sheet?

The above combine to make the task of data collection very problematic indeed. The rest of the Chapter is organised as follows: Section 4.2 presents data sources. Sample selection is presented in Section 4.3. A theoretical economic understanding of selecting financial variables is discussed in Section 4.4. The problems surrounding handling financial outliers, missing values, creative accounting practices, and hidden data are explained in Section 4.5.

## 4.2 Data Sources

The most difficult task of data collection was finding the appropriate data sources for the project. After this problem was discussed with known experts in several organisations who might have access to the information, it was decided that two of the most substantial authorities in the United Kingdom should be sought. The reason is that these authorities and in particular, The London Stock Exchange had control over the *disclosure* of activities of most registered companies in the UK. The preparation and presentation of their accounts to the public must conform to Stock Exchange Rules. The London Stock Exchange Register contains financial-statement data for both Listed and Unlisted companies on the Stock Exchange. The companies in the Register tend to be larger than in terms of total assets than are noncorporate companies. This important choice was because of initial research conducted on how to trace company information. The population chosen is not a trivial one; it represents all the major British public and private companies. The study covers the detailed financial as well as descriptive information of both listed and unlisted companies on The London Stock Exchange. A sample from the final selected companies can be found in Appendix C. Sections 4.2.1 and 4.2.2 describe two important sources of data.

### 4.2.1 The London Stock Exchange

This is the most substantial and authoritative source of biographical information about UK's financial community (Duffy, 1997; David et. al., 1997; Timbrell, 1998). The data is loaded on a CD-ROM, which holds at least five years financial reports of all companies in the UK. The reports contain a set of Balance Sheets, Income Statements (Profit and Loss Accounts), a Statement of Accounting Policies, Company Activities, Parents and Subsidiaries, Company History, Company Auditors and their Bankers. The CD-ROM is quarterly updated which reflects the state of the financial position of all the companies on the database from time to time. The CD-ROM contained over 10,000 registered companies. Registered companies are those listed on the London Stock Exchange for daily trading and public placing on their shares. The London Stock Exchange is the sole watchdog of all Listed and Unlisted registered companies in the UK.

### 4.2.2 JORDANS Financial Database of Listed and Unlisted Companies

JORDANS is a company which specialises in providing soft, high quality, company financial information online on database. The database contains detailed financial and descriptive information on 270,000 major British public and private companies. JORDANS financial database is available online at the De Montfort University Library.

The database includes:

- financial history for up to 5 years or more in most cases
- financial ratios for up to 5 years or more in most cases
- special tools integrated online to perform financial ratios calculation
- credit financial ratings for every company on the database complied by Dun and Bradstreet (Dun and Bradstreet is the leading credit reference agency in the UK)
- information about companies directors and their life style
- companies under administration or receivership
- companies currently under investigation by the DTI
- companies currently in liquidation
- companies in 'going concern situation'
- companies under bad stewardship
- companies under winding up by the Courts
- top UK 1000 companies

### 4.2.3 The Bank of England

Economic and Political data such as, interest rates, cost of borrowing, the London Inter-Bank borrowing rates, the state of the British economy, were obtained from the Bank of England. Most of the information sought is also published in the Bank's quarterly bulletins. The Chartered Institute of Bankers in England and Wales regularly publish same data information obtained officially from the Bank of England. This data is sent quarterly to associate members through the "Bankers' Journal". The author is an associate member of The Chartered Institute of Bankers.

The following are reasons why it was decided to collect non-financial information:

- ♦ Relying on financial statements of companies alone can be less meaningful because information outside the balance sheets could produce a better prediction model.
- ♦ Company directors are almost certainly economical with the truth when publishing their financial records.

- A positive or negative economic and political climate would have certain effects on the operating capabilities of most companies. For example, a rise in Corporation Tax by the UK Government would almost certainly push up operating costs of most companies. A bear economy would be bad for most companies. It could have a disastrous effect on their operating capabilities.
- The readings suggest that economic as well as political data have not been used before in using neural networks to predict corporate bankruptcies.

## 4.3 Sample Selection

There is no hard-and-fast rule that a given problem requires a sample of a certain size. However, since neural networks generalise very well when trained with a large sample (Blayo and Demartines, 1991), it is a significant step towards reducing the solution space when a huge amount of data is introduced. Training neural networks with large volumes of data tend to produce a more generalisable network. Three other important points should also be emphasised.

- *The form of the target function.* To maintain a given accuracy, sample needs to increase as the target function becomes more complex (Refenes et. al., 1993).
- *The noise in the data.* To maintain a given accuracy, sample size needs to increase as noise increases (Taylor and Lisboa, 1997).
- *Separate network for each industrial sector.* The need to have a separately trained network for each industrial sector is removed when a huge amount of data is used (Nelson and Illingworth, 1994).

The study had access to 270,000 companies. The following is a systematic description of the methods used for selecting the final sample.

**STEP 1:** Definition of period of study

The period of study identified is the collection of financial statement data of failed and healthy companies between 1992 and 1996. Economic and political data were also collected for the same period.

**Step 2:** Definition of the state of bankruptcy

Once the period of study has been defined, the author's typical definitions of bankruptcy were as follows.

- the companies which have applied for, have started, or are under the process of liquidation
- the companies which quit or have closed business
- the companies which reported the withdrawal of listing or terminated to be listed by The London Stock Exchange
- the companies which are presently under the administration of a receiver appointed by the court for the sole purpose of winding up the company in order to pay preferred creditors before closing down

The above definitions were very useful in arriving at a control sample before selecting the final training set.

**STEP 3:** Collection of Financial Statement Data

Financial statement data of failed companies were obtained from The London Stock Exchange and JORDANS financial database of major British public and private companies for five years prior to failure. The "first year before failure" is defined as the year that is included in the most recent financial statement prior to the date that the company failed. The financial statement could not be more than six months old at the date of failure. The "second year before failure" is the fiscal year preceding the first year. The third, fourth, and fifth years are similarly defined. The financial statements of healthy companies were also obtained for the same fiscal years as those of their failed mates. A "mate" is a company of the same industry and asset size in both groups. The financial statement data were then grouped according to year prior to failure. For example, if two companies failed in 1994 and 1995 respectively, and their most recent financial statements were prepared on December 31, 1993 and 1994, respectively, the first year before failure would include the 1993 statements of the former and the 1994 statements of the latter and so on. The financial statements of the healthy companies were also stratified into years before failure, corresponding to the years that were assigned to their failed mates. This was a daunting exercise.

**STEP 4:** Classify companies into their industry group

All companies, both bankrupt and healthy were classified according to their industry group. Each company was assigned a four-digit number that denoted its principal line of activity; the number system used was the Standard Industrial Classification (SIC, DTI) system of the Department of Trade and Industry in the United Kingdom. The main reason for this approach was to ensure that the required population groups were completely covered. In this study, the six main groups identified are as follows:

- the financial services industry (e.g. Banking and Investments)
- the manufacturing industry (e.g. the manufacture of products)
- the retailing industry (e.g. food retailing)
- the construction industry (e.g. road construction)
- pharmaceuticals and chemical industry (e.g. pharmacists)
- the product services industry (e.g. communications)

Public utilities groups were excluded since they are publicly financed by the taxpayers and also supported by the Government by borrowing from the financial market if necessary. Generally speaking, public utilities cannot fail.

**STEP 5:** Identify a control sample

The next step is to identify those companies from the entire population (270,000) that had failed during the time period being studied (1992 to 1996, inclusive). Once a sample of failed companies is obtained, a control sample of healthy companies which falls in the same period of study was also drawn up. Matching the failed companies with healthy companies according to their industry and size controlled the confounding influences between the two groups. For example, a random selection of bankrupt companies without regard for nonfailed companies would be totally inappropriate. The lack of use of a control sample would simply assume that the residual effects of industry and asset size are not very important. Consequently, the effect of this assumption is that the findings could seriously mis-state the predictive ability of financial ratios. It is recognised that "differences" exist among industries that prevent the direct comparison of companies from different industries. For example, the same numerical value of a ratio (e.g. liquidity ratio of 1:1) implies a different probability of failure in different industries. The evidence offered here is that ratio distributions differ among industries. It can be stated that no evidence exists to indicate that compensating differences exist.

**STEP 6:** Determine the population sample

Although five years financial statements were collected, it was only possible to use three years financial statements of both categories because it is almost impossible to predict the financial status of a company more than three years ahead. Company activities changes over time. The reason is that so many changes could have taken place in a company's fortunes within five years. For example, a company that will fail would do so within three years; if the company did not fail within three years, it means a rescue plan is in progress. A rescue plan could mean restructuring, injection of further cash, re-organisation, diversion into other activities, merger or acquisition of a competitor company.

When determining the final population sample, the author excluded companies of noncorporate form, public utilities companies, and privately owned companies with small assets size. Companies with small asset size will not have sufficient records to rely upon and will be particularly difficult for this study because they will not have all the necessary financial ratios required by the study. Although not a particular reason for exclusion from the sample, the importance of this bias is undeniable because small companies have an especially high propensity for failure (Argenti, 1976). Altman, 1968 and Taffler, 1982 suggest that new companies are likely to be excluded from most samples because they will be small and may not sufficient records to rely upon. The combined final population available for selection was 77,307 companies.

**Step 7:** Make final selection

After completing steps 1-6 above, it was possible to draw on 35,781 failed companies with full financial records dating back three years prior to the year of failure. Given that a sample of failed companies is obtained, a total sample of 41,526 nonbankrupt companies was also available for selection. A random sample of 1,250 companies were drawn up from the failed and nonbankrupt companies; thus making a combined training sample of 2,500 companies for both categories.

## 4.4 Domain Dependent Processing of Raw Data

### 4.4.1 Introduction

There are two levels of data preprocessing required when building domain dependent neural network models. The first level is domain-dependent preprocessing in which relevant features are derived from the raw data collected. The second level is generic in nature and is used to transform and shape the data into useful formats for neural networks. Both levels are critical and cannot be compromised when developing neural networks. For some problems, the raw data can be presented to the network without any work done on the part of the domain expert. However, other problems (including the corporate bankruptcy phenomenon) would benefit greatly from some domain-dependent preprocessing. This section discusses data preprocessing.

### 4.4.2 Data Preprocessing Statistical Tools

As mentioned in Chapter 6, two important data analysis and transformation tools were used to preprocess the real data used by the study. These tools are the DataSculptor™ and NeuralPredict™. These tools provide mechanisms to automatically transform user data into formats suitable for neural network training. According to Baestaens et. al., (1994) transforming the data presented to the neural network using standard statistical tools improves both learning (in time and complexity) and performance. Having the right statistical tools saves time and frustration normally encountered when building neural networks (Abu-Mostafa, 1990; Ash, 1989; Abu-Mostafa, 1994).

### 4.4.3 Preprocessing

Besides the obvious scaling of data which transforms the different time series such that each series has a mean value of zero and a statistical variance of one, some authors (e.g. Taylor and Lisboa, 1997; Hecht-Nielsen, 1990) have proposed complicated pre-processing functions. It is difficult to see how these complicated functions can have any significant effect on the ability of neural networks to carry out their mapping function. Afterall, one of the most important results in neural computation research is the proof that neural networks cope very well with noisy data (Medsker and Liebowitz, 1994; Taylor and Lisboa, 1997).

A careful start in the process of handling data presented to neural networks is to clean the data and then transform the database. After consulting the works of many researchers in the field, (e.g. Refenes et. al., 1992; Baestaens et. al., 1994; Medsker et. al., 1996) the author adopted the following standard procedures for pre-processing of the data presented to the neural networks used in the study.

#### 4.4.3.1 Detrending

The first useful start for dealing with financial data in particular is to remove seasonal and/or general trends from the data. The reason for taking this approach is that the existence of strong trends in the independent and dependent variables (e.g. financial and economic) can lead to spurious correlations and regressions because it is easier for the network to learn the *general* features of the data than the *actual* relationship between the variables. The only occasion where this could have been faced by the study is in the case of seasonal sales (corporate turnover as inputs). However, since the sales turnover presented to the network was in ratio form, the networks used in this study can only learn the actual relationship between the variables. Using the ratio form would have removed seasonal trends in the data anyway. More generally, it is unwise to submit absolute raw values to neural networks which will trend upwards or downwards over time. Instead it is suggested that a ratio such as (turnover)/(average stock) which does not trend over time should be used. Detrending is mentioned in order to show that the study is aware of this particular problem. Nonetheless, the study did not have to deal with this particular problem.

#### 4.4.3.2 Set Noise Level in Data

The standard statistical tools mentioned in Section 4.4.2 above allow the author to chose the appropriate level of noise in the data to be presented to the network. Since the nature of the data presented to the networks can be regarded as "inconsistent behavioural data", the author specified "very noisy data level" in the dialog box in NeuralPredict™. Having a high noise level inhibits overfitting of the model to the data presented to the networks and promotes better generalisation. This stage is very important in the preprocessing mode so that when the data transformation is completed, the distribution of each input variable to the networks will be uniform.

#### 4.4.3.4 Transforming the Data

Converting numerical and symbolic inputs into a form suitable for neural networks is an iterative process that interacts with the entire development process. This subsection addresses two crucial issues: transforming enumerated and continuos data.

#### 4.4.3.4.1 Enumerated Data Transformations

Neural networks do not accept symbolic data and as such enumerated data must be transformed. Symbolic fields are most easily identified forms of enumerated data. A common approach is to use a single digit to represent symbolic data inputs. There are several methods for handling enumerated data such as continuos encoding, binary encoding and one-of-N code. This study adopted the one-of-N code. The reason for adopting the one-of-N code is that it is the most appropriate method for handling enumerated data which has no natural ranking. The obvious characteristic of financial data is that they do not have natural ranking. One-of-N codes are fine when there are few possible enumerated values. It is commonly accepted that translating the enumerated numeric fields into one-of-N codes improves generalisation performance.

#### 4.4.3.4.2 Continuous Numeric Transformations

The performance of a neural network model is often improved by transforming the continuous numeric inputs (Baestaens et. al., 1994). The primary purpose of transforming numeric inputs it to modify the distribution of the explanatory variables. Continuos transforms of input variables are typically scaled into the range [0, 1], this interval provides the maximum gradient descent adaptation as the inputs deviates from the average (Bishop, 1995). However, a target output that falls outside this range will constantly create large propagated errors and the network will be unable to learn the input-output relationship implied by the particular training pattern.

Finally, the efficiency of the learning procedure in terms of optimal generalisation capability of the network can be taken as a core component but necessarily the most critical aspect. Properly preprocessing of data for neural networks should always be given serious consideration prior to training. Although it is not essential in certain cases, it is vital in the corporate bankruptcy phenomenon.

## 4.5 Handling Missing Values

### 4.5.1 Introduction

Intuitively, when financial statement data are processed and analysed, there are always multivariate problems such as outliers, missing values, hidden data and creative accounting practices. These problems must be dealt with if a proper input representation to neural networks is planned. This section presents methods for dealing with missing values in financial data.

### 4.5.2 Dealing with this Particular Problem

Although there were only 11 cases in the entire data sets where missing values occurred. There were 6 six cases where the problem was due to transfer of data from the database to Excel. These cases were quickly dealt with by revisiting the original database again and then re-transfer the data. However, the remaining five cases were rather problematical. The discussion that follows shows how these problems were dealt with by the study.

Some researchers (e.g. Jensen, 1992, Hill et. al., 1992) suggest that an averaging method can be applied to fill in the missing value with the average of the last value and the next valid value. The practical difficulty with this approach is that averaging may be inappropriate because financial parameters are not determined by trend within periods, but by taking into consideration various activities of the company and pronouncements by the Accounting Standards Board (ASB) (David et. al., 1997). For example, a company may pay corporation tax for 1994 at £34m and 1996 at £40m but report losses in 1995 and may not suffer any corporation tax on profits for the period. To apply averaging in this case would be misleading. Further, corporation tax payable on profits in one period often bears little or no relationship with the tax payable in another period. The study applied the provisions of the Acts, UKGAAP and the pronouncements of the ASB to deal with specific missing values. For example, the rate of corporation tax for the period was applied to find the missing value instead of taking the average value of two periods to find the missing value.

Lev and Sunder (1979) suggest that one could use the mean, maximum, or minimum of the entire field. This approach again is fraught with difficulties. Companies operate in accordance with certain policies, which vary between accounting periods as agreed by the directors at Board meetings. Having said that, accounting policies are prepared in the interest of the company and therefore vary according to the issues facing the company at a particular point in time. To apply the minimum or maximum of the entire field would be totally misleading. It is therefore important that accounting data should be reflected accordingly in the period in which they occur.

Alici and Gifford (1995) suggested that where the field contains categorical data for different periods and there is a missing value in the category of one period, another category should be created. It will be inappropriate to create another category because two categories may represent separate performance indicators. Further, the danger with this approach is that this could blur the difference between a failed company and a healthy company. It is also fraudulent and illegal to create another category. Investors and other users of the company's financial statements rely heavily on every single of the statement and deceive them will carry dire financial consequences to the company because investors and other users are quick to file court proceedings if they suffer financial loss on misleading information.

Baba and Kozaki, (1992) suggest that if the field contains numerical data, one should create an enumerated field to mark records with the original field missing. To do this would disregard the characteristics of the underlying stochastic processes generating the missing value. For example, annual depreciation affects the value of fixed assets as disclosed in financial statements. If this underlying information is disregarded when dealing with missing values, the results obtained may be erroneous. Financial statements should be regarded as sensitive statements and recorded properly. The more accurate the missing value deduced the better the resulting network.

Finally, the treatment of these five cases was then sent to an independent expert for a second opinion. There were no disagreement reported. As mentioned earlier, the other 6 cases were simply re-transfer from the original database to Excel for further processing.

### 4.6 Input Parameters

The specific input variables reported in this section have been selected based on domain knowledge of the author. In addition, some of the variables selected have also been mentioned regularly mentioned in the literature (e.g. Berry and Treiguiros, 1991) as having greater explanatory predictive power in identifying impending corporate bankruptcies. The combination of these specific variables with the independent variables selected would tend to produce a better of neural network.

| Section | No. | Financial Ratio | 1994 | 1995 | 1996 |
|---|---|---|---|---|---|
| **Financial Summary** | 1 | Turnover | x | x | x |
| | 2 | Pre-tax Profits | x | x | x |
| | 3 | Dividends | x | x | x |
| | 4 | Retained Profits | x | x | x |
| | 5 | Shareholders Funds | x | x | x |
| | 6 | Capital Employed | x | x | x |
| **Profit and Loss** | 7 | Turnover | x | x | x |
| | 8 | Cost of Sales | x | x | x |
| | 9 | Total Expenses | x | x | x |
| | 10 | Gross Profit | x | x | x |
| | 11 | Depreciation | x | x | x |
| | 12 | Other Expenses | x | x | x |
| | 13 | Operating Profit | x | x | x |
| | 14 | Other Income | x | x | x |
| **Balance Sheet** | 15 | Total Reserves | x | x | x |
| | 16 | Issued Capital | x | x | x |
| | 17 | Long Term Debts | x | x | x |
| | 18 | Working Capital | x | x | x |
| | 19 | Net Tangible Assets | x | x | x |
| | 20 | Corporation Tax | x | x | x |
| | 21 | Bank Overdraft | x | x | x |

| | | | | | |
|---|---|---|---|---|---|
| | 22 | Trade Creditors | x | x | x |
| | 23 | Trade Debtors | x | x | x |
| | 24 | Total Assets | x | x | x |
| **Stability** | 25 | Profitability Margin | x | x | x |
| | 26 | Return on Shareholders Funds | x | x | x |
| | 27 | Return on Capital Employed | x | x | x |
| | 28 | Return on Total Assets | x | x | x |
| | 29 | Interest Cover | x | x | x |
| | 30 | Stock Turnover | x | x | x |
| | 31 | Current Ratio | x | x | x |
| | 32 | Liquidity Ratio | x | x | x |
| | 33 | Solvency Ratio | x | x | x |
| | 34 | Asset Cover | x | x | x |
| | 35 | Gearing | x | x | x |
| | 36 | Debtors Turnover | x | x | x |
| | 37 | Net Assets Turnover | x | x | x |
| | 38 | Turnover Per Employee | x | x | x |
| | 39 | Profit Per Employee | x | x | x |
| | 40 | Creditors Payment Period | x | x | x |
| | 41 | Working Capital Per Employee | x | x | x |
| | 42 | Shareholder Liquidity Ratio | x | x | x |
| | 43 | Total Assets Per Employee | x | x | x |
| | 44 | Total Reserves | x | x | x |
| **Cash Flow** | 45 | Operating Profit | x | x | x |
| | 46 | Taxation | x | x | x |
| | 47 | Dividends | x | x | x |
| | 48 | Stocks | x | x | x |
| | 49 | Debtors | x | x | x |
| | 50 | Bank Deposits | x | x | x |
| | 51 | Creditors | x | x | x |
| | 52 | Overdrafts | x | x | x |
| | 53 | Loans | x | x | x |
| | 54 | Total Reserves | x | x | x |

| | | | | | |
|---|---|---|---|---|---|
| ***Economic** | 55 | Annual Inflation | x | x | x |
| | 56 | LIBOR | x | x | x |
| | 57 | LIBR | x | x | x |
| | 58 | Economy | x | x | x |

- LIBOR: London Inter-Banks Borrowing Rates (borrowing rates between banks)
- BBR: Bank of England Borrowing Rates
- AIR: Bank of England Annual Inflation Rate
- Economy: Bank of England state of British economy forecast

NB: There is the assumption for average rise in the index for economic and political factors data.

Table 4.1 Contains 54 Input Variables selected for each year

## 4.7 Summary and Conclusions

The collection of data for bankruptcy study requires a definition of failure and specification of the population sample from which companies are drawn. The detection of company operating and financial difficulties is a subject which has been particularly susceptible to financial ratio analysis. The significant of selecting the appropriate financial rations for the modelling of corporate failure cannot be overemphasised. Although ratio analysis may provide useful information, financial ratios must be used with discretion since not all ratios predict equally well. The art of the matter is the selection of those financial ratios that are deemed important in the modelling process. Domain knowledge should be used in selecting appropriate financial ratios because this approach would ensure that the relational implications of different ratios are accounted for properly in accordance with domain expert knowledge.

Researchers can improve on the validity of their analyses by matching samples of failing and healthy firms by size and industry and also, by taking care that economic theories are constantly applied in their empirical research in financial prediction. The properties of accounting numbers do not permit any models with few parameters to capture the irregularities in financial ratios due to their stochastic nature. The complexities surrounding corporate failure do not permit few parameters to be examined and analysed as input representations to neural network. We propose that there should be sound economic understanding of variables so that spurious correlations in data can be identified since their effect can tend to produce a less meaningful and effective application.

Although the efficiency of the learning procedure in terms of multivariate predictive capability is the core component of any successful application, it is not necessarily the most critical one. Approaches in pre-processing input data for neural networks should always be given serious consideration from the outset prior to training neural networks. This can be regarded as vital and significant in majority of cases, although, it may not necessarily be so in certain cases depending upon the nature of the problem.

# Chapter 5

## Neural Network Design Considerations and Selecting the Topology

### 5.1 Introduction

The selection of a specific neural network topology for use in a particular domain such as corporate bankruptcy prediction involves the difficult task of constructing a large number of neural network topologies with different structures and parameter values before arriving at an acceptable model. The task is to choose a functional neural network from a number of possibly competing alternatives, and to estimate parameter values in a manner that can be possible. However, the context of the problem is that there are no fixed rules involved in determining the appropriate architecture or its parameter values (Weigend et. al., 1990). The trial and error process can be tedious and time consuming and yet, this process is particularly significant in deriving a good model.

Neural network topology selection refers to a systematic procedure for selecting between competing models (Werbos, 1988). Naturally, it is regarded as a key aspect in optimisation and replicability of neural network performance. Taylor and Lisboa (1997) argue that over the years of development of the neural network field a large number of model selection procedures have been proposed. The unpredictable interactions of numerous design considerations would depend largely on the network methodology chosen. The success or failure of the methodology chosen would have a direct impact on the final neural network topology. This chapter attempts to give a categorisation of the different procedures along with some characteristic examples.

From the outset, it is essential that the general taxonomy of the neural network architectures to be constructed is determined. This is important for data organisation and parameterisation issues to be considered alongside network construction. However in particular, the general taxonomy of temporal processing architectures subsumes much existing architecture in literature and points to other neural network architectures discussed in literature. The determinations of the general taxonomy of neural network architectures for financial time series prediction can be very difficult (Lapedes and Farber, 1988; Weigend et. al., 1990; Weigend and Srivastava, 1995). These difficulties can be accounted for since companies activities vary greatly over a number of periods. Therefore, in order to capture and account for this changing business activities of companies, precise network taxonomy must be established before network construction algorithms can begin. The particular type of algorithm chosen depends on the solution space.

Next in the taxonomy consideration is the network framework (Mozer, 1993). The basic framework for a temporal prediction network is to have training data separated into the relevant period they are related to discrete compartments, a sensible assumption, since financial time series data are intrinsically discrete, and continuos series can be sampled at a fixed interval. Prediction involves two conceptually distinct components. The first is to construct a neural network that will act as short-term memory that retains aspects of the input sequence relevant to making predictions. The second makes a prediction based on the short-term memory. Applying this taxonomy to a neural network framework, the predictor will always be a feedforward component of the network, while the short-term memory will often have internal recurrent (historical) connections (Tsypkin, 1973).

Temporal processing is a particularly challenging problem because conventional neural network architectures and algorithms are not well suited for patterns that vary over time (Feldman and Ballard, 1982; Abu-Mostafa, 1990). The prototypical use of neural networks is in structural pattern recognition. In this case, a collection of features (e.g. assets, liabilities, or otherwise) is presented to a network and the network must categorise the input feature pattern as belonging to one or more classes. For example, a network might be trained to classify companies based on a set of attributes describing financial indicators such as "positive," "negative," or "no change"; or a network can be trained to recognise failure indicators in the financial statements of current operating companies. In these circumstances, the network is presented with all the relevant information simultaneously.

Constructing reliable time series models for evaluating corporate financial performance is a challenging prospect because business activities of companies do not follow a random walk but a chaotic one. Also, experimental studies of human performance in short-term memory recall, probability of estimation, and rule inference from examples, lead to predictions that in their present work environment and settings, forecasters are likely to make serious errors of judgement. Often, these errors can be catastrophic.

Financial analysts themselves express uncertainty about how best to construct time series processing models since their present score cards in use for evaluating corporate performance are no longer practicable. One particular reason put forward is that score cards techniques do not show any improvement in forecasting skill over different periods despite improvement in quality and quantity of guidance information. This chapter will put forward a number of neural network architectures for processing time series data.

The rest of this chapter proceeds as follows: Section 5.2 presents domain knowledge and neural network heuristics. Topological considerations and its impact on neural network construction are presented in section 5.3. The various neural network topologies considered during the modelling process are presented in section 5.4. The reasons for selecting a particular architecture are discussed in section 5.5.

## 5.2 Domain Knowledge and Neural Network Heuristics

The integration of domain knowledge into neural network architectures holds great promise in solving complicated real world problems (Kohara and Ishikawa, 1994). The most popularly known approach is to insert prior knowledge in an initial neural network architecture and refine it with learning by examples (Treleaven and Goonatilake, 1991). The learning examples in this case will be the known financial statements of companies published annually. According to Wood and Piesse (1988), the evidence that accurate discrimination in samples of failed and non-failed companies using published financial statements is possible is substantial. Employing domain knowledge into neural network heuristics ensures that only those data which are relevant are introduced to the network anyway. The network is then forced to train on those pre-selected data.

The awareness of the complex inter-relations between 'neural network engineering' parameters and network performance is an essential ingredient of successful application development. Domain knowledge plays a significant role in identifying these important features. Successful application development, however, is not straightforward. It involves a considerable degree of expertise in three main areas.

First, a good deal of knowledge and practical experience in the domain area is very useful particularly in identifying and selecting essential explanatory variables. This is crucial in the application development process. For example, in developing an application of neural networks to process loan applications, expertise in the area of accounting and banking are invaluable. There will always be a difference in fundamental emphasis between the application developed by domain expert and domain independent models. The awareness of the complex relationships between input units and network generalisation would remain a distinguishing feature in financial engineering.

Second, a good deal of familiarity with the application is required to achieve good generalisation performance. Important factors are choice of financial, economic as well as political indicators, their significance and correlation, their interconnectivity and permutations, their relationships with the desired output; the pre-processing, normalisation and optimisation of multi-parameter datasets, and the network performance.

Third, achieving good network performance involves extensive experimentation with network design and fine-tuning of control parameters, such as learning rules, transfer functions, and weights updates. It involves a good deal of knowledge and fluency with different types of data and their associated control parameters.

This thesis asserts that extensive knowledge of the domain is required when designing neural networks in the application area of financial modelling. One argument against domain-independent analysis in designing neural network architectures is based on the very premise that makes it possible. Ignoring cases involving other areas of financial modelling (such as, share prices and currency rates prediction), this scepticism exits for a number of reasons; many of which are explained by the use of domain-independent models. The domain-independent analysts claim that prior knowledge in the domain is not required in constructing neural network architectures since neural networks will always find associations in the data submitted for training. Detractors from this point of view argue that, since neural networks are universal approximators domain knowledge is crucial in the application development process (Caruana, 1993).

Rose et. al., (1982) showed that domain knowledge in constructing neural network topologies is an essential ingredient in application of neural networks in the financial domain area. Kohara and Ishikawa, (1994) argue that the success of neural networks in many application areas is due to some specific features, such as, prior knowledge, practical experience of the developer in the application area, and example-driven training. It was argued further that, neural structures can embed in their connection data-intrinsic relations that complex theoretical models could not state explicitly.

The prevailing neural network models of corporate failure prediction are based on the knowledge of individual researchers (Scott, 1981). A successful financial application of neural networks requires the synergetic combination of expertise in financial engineering and neural network engineering. Domain knowledge will always play a crucial role in the design of neural network architectures since the inherent relationships between indicators of corporate prediction are overwhelmingly complex and rigid.

Clearly, all the aforementioned issues are inter-dependent. Handling the above problems and producing a reliable and practical model is neither a straightforward nor an easy procedure. If the appropriate architecture can be achieved, financial analysts would benefit mostly since a robust system of neural network will inevitably put them ahead of the game. However, it is even less assuring if during the development process domain-independent is assumed. Section 5.3 will now consider neural network design considerations.

## 5.3 Design Related Considerations

### 5.3.1 Overview

Financial analysts have the desire to produce a neural network model that would be very effective in application. The reason for this desire is to be able to identify those companies that are most likely to fail so that they could advise their clients accordingly. The difficulty with this prospect lies in the ability to construct the appropriate neural network model. What follows are the design related considerations that should be considered when determining the appropriate neural network model.

### 5.3.2 Neural Network Design Considerations

Many of the rules which govern corporate failure prediction are qualitative or fuzzy, requiring judgement, and hence by definition are not susceptible to purely quantitative analysis. Five main performance measures are usually considered when designing neural networks. These performance measures and their controlling mechanisms are very important considerations in order to produce a good model of neural network.

### 5.3.3 Network Performance Measures

As mentioned in section 5.3.2, designing neural networks are subject to five performance measures. These measures are now discussed in turn below. Recall that these listed performance measures also depends on the scale of the problem, therefore the more difficult the underlying phenomenon, the more stringent the criteria threshold.

- Convergence
- Generalisation
- Stability
- Scalability
- Sensitivity

According to Simpson (1990) convergence concerns the problem of whether the paradigm chosen is capable of learning the classification defined in dataset and under what conditions it does so, and what are the computational requirements for convergence. Simple, straightforward architectures with small samples prove convergence to be easily attained because the architecture itself is less complicated. The reason for this is that as training continues; the gradient method will tend to zero very quickly. On the other hand, complex architectures with large datasets prove convergence less likely possible and as training iteration increases, the gradient descent method will tend to move away from zero. This sharp contrast is the obvious dilemma. The controlling circumstance in this situation will be to strike a balance between network complexity, network parameterisation, and the underlying phenomenon.

Generalisation measures the ability of neural networks to recognise patterns outside the training set (Shepanski, 1988). When designing neural networks, the ability of the network to generalise very well from unseen data is critical to the whole application development. Indeed the most essential feature of a learning machine is its ability to generalise over the task domain when presented with unseen dataset. Moyer, (1977) and Moody, (1992) suggested that neural networks generalisation performance on real-world problems is difficult to achieve unless some a *priori* knowledge about the task domain is built into the system.

Scalability concerns both convergence and generalisation. By scaling up a network, convergence and generalisation issues are considered concurrently. The issues to be put into consideration here is the time and training iterations it would take to achieve convergence. If the generalisation performance of the network is poor, the related issue would be the number of network parameters to be affected before convergence and generalisation can be achieved together. These are no simple tasks.

Stability concerns the consistency of the results produced by neural networks when varying the values of the parameters that influence their performance (Refenes and Azema-Barac, 1993). The design consideration concern is that the datasets used to train the network should be processed carefully so that when varying parameter values the results of the network will not change significantly. However, neural networks, like most non-linear systems, have been known to produce wide variations in their predictive properties (Abu-Mostafa, 1994). The other concern here is that small change in the network design; learning rules, transfer functions and number of training times may produce large changes in the network behaviour. However, it is often desirable to identify intervals of values for these parameters that give statistically stable results across different training and test sets. Although financial data do not follow known regularities because of its temporal nature. What need to be established in this regard are the intrinsic values of the data rather than the identification of the intervals value of network parameters. It is important that the intrinsic values of the parameters are identified purely on the basis of expertise in financial engineering, and also to demonstrate that these identified parameters values persist across different data sets.

Sensitivity is the ultimate performance metric for any model of financial application (Chauvin, 1989). Its usefulness as a quantitative decision-making tool in financial decision making is enormous. The main goal of a financial analyst is to use the eventual model to simulate 'what if' scenarios, and the ability to have a formal framework for reasoning about the model's multivariate prediction ability. It is possible to use a trained financial model of neural network to conduct adequate sensitivity analysis without recourse to statistical approaches. The practical benefit of using a trained neural network to do this is huge. What needs to be done to do this is to select four control mechanisms (e.g. such as the activation function, cost the function, learning rules, and transfer function) to conduct a detailed sensitivity analysis. Each control mechanism will be edited to reveal detail insight into the network performance so that when evaluating the 'what if' scenarios parameter values can be adjusted accordingly.

Convergence, generalisation, and neural network design would remain the most important experimentation tasks of neural network training. It is suggested that generalisation is the main property of design consideration since it determines the amount of data needed to train the network. The performance measures had to be considered in turn before selecting the appropriate topology. The topologies considered in this study are discussed in section 5.4 below.

## 5.4 Topology Selection

The selection of a particular architecture from a number of topologies constructed depends on the nature of the problem and what the network is expected to perform. The architecture of a neural network is defined by the arrangement of its input units, and its cognitive characteristics. This study now presents various topologies considered as part of this research. The topologies are described in turn and the rationale for their selection or rejection follows from their description.

### 5.4.1 Topology 1

The topology shown in figure 5.1 below is the multilayered feedforward neural network. There is a forward pass from the input units to the first input layer. The hidden layers are fully connected and there is one output layer. It is commonly agreed that this topology is used to learn and predict time series.

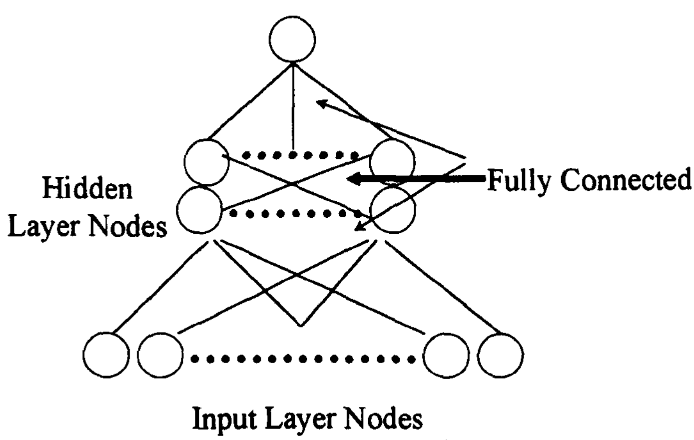



**Figure 5.1 Simple, straightforward neural network architecture**

#### 5.4.1.1 Rationale for Topology 1

As mentioned earlier, the rationale for topology 1 is that it has been extensively used to process time series in financial data. The architecture tends to submit all possible input units. The serious drawback using this topology has been reported in Weigend and Srivastava, (1995) and Weigend et. al., (1991). The authors suggested that the topology would have serious difficulties in processing time series. In addition, it is popularly used for domain-independent applications where little knowledge in the particular domain is required.

#### 5.4.1.2 Reasons for Rejecting Topology 1

The architecture is simple and will not be suitable, under normal circumstances, when there is the requirement for long term prediction. It is particularly useful for single point prediction. However, the objective of the study is to produce an architecture that will process time series in financial data. The above topology will tend to carry too many weights and as such will have high computational power with limited generalisation capability. It may be successful in learning the training set but will be less effective in application. According to Trippi and Turban (1996), this type of architecture would fit the training data too closely and as such would not predict accurately as it is expected. In addition, Bose and Liang (1996) suggested that this type of architecture tends to overfit training dataset.

In addition to the aforementioned points, topology 1 is rejected because it will be difficult to use in this study since datasets will be organised in the eventual network according to domain knowledge. The aim was always to organise data in the manner financial analysts evaluates corporate performance.

### 5.4.2 Topology 2

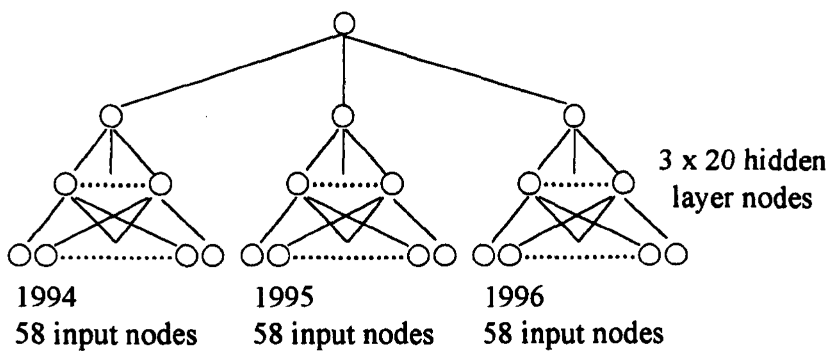



**FIG.5.2 Network architecture using time series aspect of data**

#### 5.4.2.1 Rationale for Topology 2

The above neural network architecture for topology 2 uses time series aspect of data. Each sub-network will have 58 input nodes. The three sub-networks will be trained separately so that the output neuron from each sub-network is connected to what can be regarded as the final output layer (central output point). Using this approach, there is no exchange of information between the sub-networks, the final output layer is thus regarded as an information collection centre with no further processing.

#### 5.4.2.2 Reasons for Rejecting Topology 2

Although there are several reasons that could be advanced for rejecting topology 2; however, three main reasons are identified in this section.

1. The network does not use domain knowledge about groupings of variables. However, it is the practice of practitioners to group financial variables according to their significance in order to assign appropriate weights to their groupings.
2. The time series element is only modelled very weakly. The additional output neuron is only used as a collecting point rather than a further processing centre. Information is not shared between sub-networks and the output neurons are only a matter of simple addition of the results of three sub-networks.

3. Within a non-linear context, specifically that of modelling time series using neural networks, this architecture will require longer training iterations and several levels of network parameterisation to converge. The architecture looks too awkward and ambiguous.

Section 5.4.3. now presents topology 3 which is forward pass but has no hidden layer.

### 5.4.3 Topology 3

The neural network topology as shown in Fig. 5.5 is concerned with bringing domain knowledge analysis into optimising neural network topologies. The architecture shows a forward pass that resembles cascade correlation networks. It does not use a middle-hidden layer but simply connects to the output layer. There is no backward propagation of errors either.

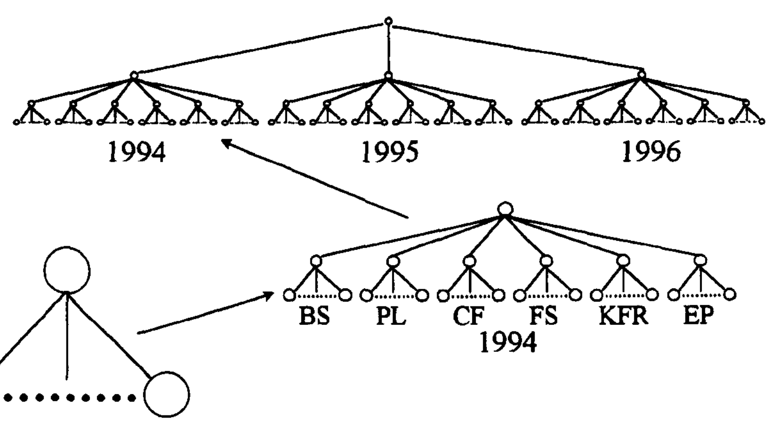



**FIG. 5.3 Network architecture using domain knowledge to organise data**

#### 5.4.3.1 Rationale

The network architecture for topology 3 uses domain knowledge to organise data, however, with a very weak time series processing or tendency. It looks sufficiently complex to capture irregularities in the datasets but with no backward propagation of errors. Each sub-network contains five adjacent networks representing five facets of failure. Therefore, in each sub-network for each year, there is Balance Sheet network, Profit and Loss network, Cash Flow network, Financial Summary network, Key Financial Ratios network and Economic and political factors network. Each sub-network is trained independently of each other and the output from each independent network is connected to one central output layer. The additional output layer is the results of the output layer from each of the sub-networks, which represents the overall final prediction. This approach does not share information between sub-networks but uses the additional output layer as a mere collection centre, which represents its prediction.

#### 5.4.3.2 Reasons for Rejecting Topology 3

Topology 3 is however rejected for the following reasons:

- The network is too simplistic since it carries too few weights. The effect of this is that the network will have less computational power and may find it difficult in handling huge amounts of data. The network may not learn the training datasets well enough to have any multivariate prediction ability.

- Data is too compartmentalised. The success of applying a neural network to solve a particular problem domain depends upon the organisation of datasets. The success or failure would depend upon whether the network is able to train on a particular data arrangement.

- The topology loses power of neural networks to make associations between different variables.

- There is no relational approach in groupings of variables and as such no information shared between variables. The use of one central collection point for the processing final output is not particularly useful.

#### 5.4.4 Topology 4

The neural network topology as shown in Fig. 5.4 is concerned with integrating domain expert knowledge into an artificial neural network architecture using an extra hidden layer. Although hidden layers are feature extractors, they give computational power to the network in order to improve their multivariate prediction ability.

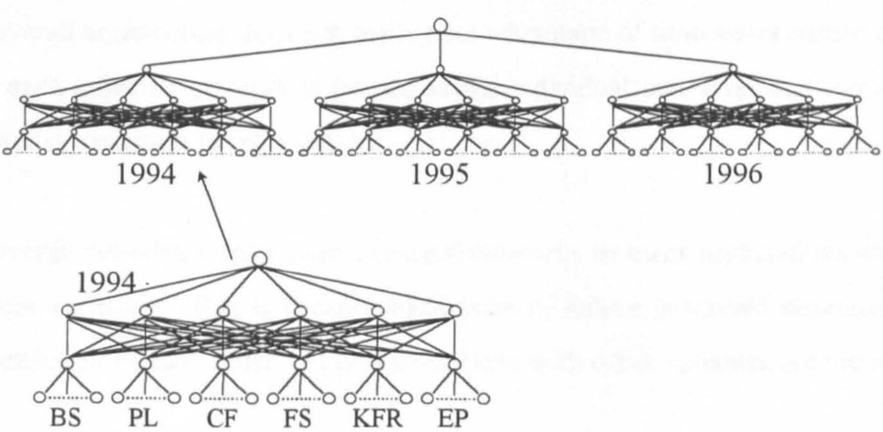



**FIG. 5.4 Neural network architecture using extra hidden layer**

##### 5.4.4.1 Rationale

There are three sub-networks representing the periods, 1994, 1995, and 1996. Each sub-network is made of five adjacent networks representing the Balance Sheet network, the Profit and Loss Account network, the Cash Flow network, the Financial Summary network, the Key Financial Ratios network, and the Economic and Political factors network. These adjacent networks although coupled together but not linked at the input level represents five facets of predicting corporate failure. It is commonly agreed that the use of an additional hidden layer will give the network extra computational power.

#### 5.4.4.2 Reasons for Rejecting Topology 4

The topology uses domain knowledge
This architecture supports the use of an extra hidden layer, however, it is rejected for the following reasons.

- The architecture is very weak in modelling of time. The objective of this research is to produce an architecture that will model time varying effects effectively.

- The overall architecture does not really take advantage of time series nature of data since each adjacent network is trained at the individual unit level and there is no effective distribution of information.

- The overall network loses power of neural networks to make associations between different variables. This is because each facet of failure is trained separately and independently of each other and no associations with other variables are recorded.

- The relationships that exist between the sub-networks are not adequately accounted for in a manner that is consistent with financial analysis.

### 5.4.5 Topology 5

The neural network topology as shown in Fig. 5.5 is concerned with the following features.

- Building a neural network that will allow the use of domain knowledge and neural heuristics to improve multivariate prediction ability.

- The architecture processes time-varying patterns since it uses short term memory that holds on to relevant past events and associator that uses the short term memory to classify or predict.

- It is possible to provide adequate account of the changing nature of business activities in the neural network. This will have a major impact in combining expert domain knowledge and artificial neural networks for the prediction of corporate bankruptcies.

- The architecture is consistent with the practice of financial managers in the use of traditional methods for identifying perilous conditions of bankruptcy in the financial statements of current operating companies.

- The architecture allows dozens of technical and fundamental indicators of bankruptcy on the basis of which they try to predict financial time series.

- The architecture allows for the compartmentalisation of technical and fundamental indicators of financial time series into three separate years so that the sub-network of each can be trained separately and then connected to its immediate neighbour. This approach allows for information about relevant past events to be shared between the independently trained sub-networks.

- The architecture introduces the use of two fully connected hidden layers.

The architecture in figure 5.5 is a multilayered feedforward neural network with the backpropagation algorithm. There is a forward pass from the input units to the first hidden layer. It introduces the use of two fully connected hidden layers and output layer. It consists of three sub-networks. (or a series of 18 tightly coupled networks) compartmentalised into three years. There is one sub-network for each year. Each sub-network is connected to its immediate neighbours. In addition, the first hidden layer of the 1995 sub-network receives additional information from the previous 1994 sub-network. The first hidden layer of the 1996 sub-network receives additional information from the output of the 1995 sub-network.

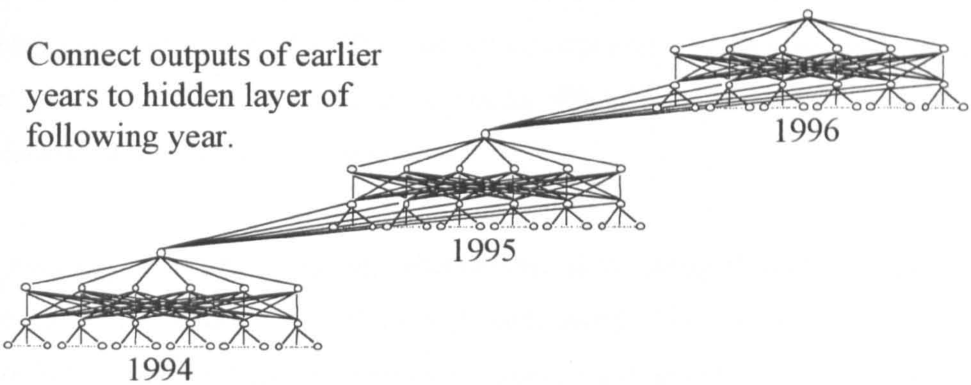



**Figure 5.5 Inter-connected sub-networks to measure temporal tendencies**

#### 5.4.5.2 Rationale for Topology 5

The topology uses domain knowledge to organise data and it appears to have a high time series processing or tendency. It has the following important features for the study.

1. The architecture embodies most of the relevant characteristics of the problem based on domain knowledge.
2. High level topology captures temporal nature of data.
3. Low level topology of sub-networks uses domain knowledge.
4. There is obvious interconnectedness in the hidden layer.
5. It puts more emphasis on current conditions and progressive less emphasis on distant (in time) conditions. However, the architecture is still somewhat compartmentalised.

## 5.5 Summary

The selection of a preferred topology for use in a particular domain involves a number of difficult tasks. The first task is to construct a large number of neural network topologies with different structures and parameter value consideration in mind when constructing the models. The next difficult is to chose between competing alternatives on their face value. Having said all that there are no fixed rules involved in determining the acceptable model. The trial and error process can be quite painstaking and time consuming. However daunting it may be, this process remains the important part of the neural network modelling process.

Before selecting between competing alternatives, it is essential that the general taxonomy of the topologies involved is clearly understood. The reason for this is that there should be a balance between network complexity and what they can do. Having said that, the general taxonomy of neural network topologies designed to process time series in financial data is somewhat different from simple architectures that are simply designed to predict the next time step. What makes it different includes, data organisation, network connectivity, parameterisation and use of hidden layers. This combination makes the whole exercises even more difficult and time consuming.

This chapter has presented five different neural network topologies. The reasons for rejecting four of the topologies had been carefully explained. The study selected neural network topology 5 because it will allow the author to process time series properly. It also allows domain expert knowledge to be used in data organisation.

The following chapter will now present implementation of the study.

## CHAPTER 6

## IMPLEMENTATION

### 6.1 Introduction

It has been stated in the previous chapter that the selection of a specific neural network topology for use in a particular domain involves the difficult task of constructing a large number of neural architectures with different structures and parameter values before arriving at an acceptable model. The other concern (as alluded in Chapter 5) is to determine the general taxonomy of the neural network architectures to be used. As soon as the above tasks have been completed, the neural network development approach should be implemented. This chapter addresses this important phase.

The implementation stage should provide the possible functionality of the neural network architecture, and the software packages which are needed to achieve this aim. The software needed to implement the study should allow the author to carry out the following tasks efficiently.

- data retrieval, analysis and transformation
- neural network architectures creation
- the organisation of data in the input layer
- paradigm selection
- the display of any information to the developer
- the submission of prediction for interpretation.

There are a number of software packages which have been especially developed to allow the use of large-scale data, the building of complex neural network architectures and the selection of a particular paradigm for the investigation. This study used DataSculptor, NeuralNetworks Predict, to process the data for neural network inputs, and NeuralNetworks Professional Development PLUS to implement the neural network architecture (see Appendix H). A ratio and Cash flow Analysis software supplied by Red Sun Associates (see Appendix F) was also used to calculate financial summary analysis automatically.

The organisation of this chapter proceeds as follows. Section 6.2 examines the software packages used in detail, covers the capturing of user knowledge and the displaying of information to the user. Section 6.3 covers the network training process.

## 6.2 Neural Network Implementation

The implementation phase will firstly discuss the development environment and then neural network characteristics. What follows is the development environment.

### 6.2.1 NeuralWare DataSculptor Software

DataSculptor is a software package written by NeuralWare™ the leading supplier of development tools for neural network applications and is available 'off the shelf'. DataSculptor is a data retrieval, analysis, and transformation system. Using an intuitive interface, it allows access to data in many popular program formats. It was designed to handle any level of data for pre-processing. It was used in the study to pre-process the huge amounts of data because of the range of utilities that it offers.

### 6.2.2 Neural Works Predict Software

Predict is a development tool produced by NeuralWare.™ This tool integrates all the components needed to apply neural networks to a variety of problems. It is different from other neural network packages because it automates much of the painstaking manipulation, selection, and pruning of data that takes up most of the time in building a real-world neural network application. This product was used in addition to DataSculptor because of its advanced and expert data processing platforms for handling noise in data. It was particularly useful for this study in dealing with the problems associated with huge symbolic data fields and one-of-N categorisation.

### 6.2.3 Neural Works Professional Development System/2 V.5.2

NeuralWorks Professional Plus is a standard neural network development system (NeuralWare™). It allows building of complex network architectures, training, refining, and deploying neural network solutions. It is very powerful and highly flexible. The following features are supported:

- allows many learning algorithms
- can handle any level of data
- can normalise any level of data using the MinMax tables
- allows customisation of any level of network architecture
- offers easy to use graphical interface
- instantly creates ANSI standard C code to deploy a fully trained network thus removing the need to write a network

For completeness, the diagram shown in Fig. 6.1 explains the relationships between the various software packages selected for this study.

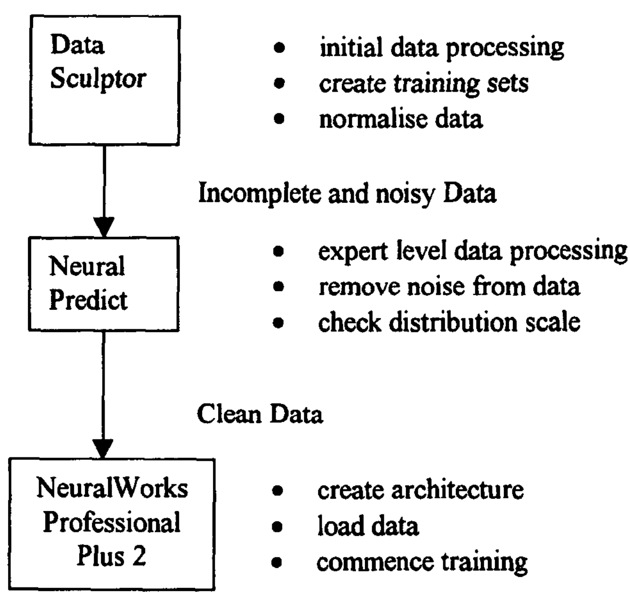



**Fig.6.1 Neural Network Development Environment**

## 6.3 Network Training Process

The following is a step-by-step description of the network training process.

**Step 1:** Select training sets

As already mentioned, the final selection comprises processed data for 2,500 companies. This total is divided into three parts: a training set of 1,350 companies, a test set of 400 companies, and a validation set of 750 companies. The data sets were selected randomly from a large population sample of 270,000 companies as discussed in Chapter 3. The training set was chosen so that it represented equally the likelihood of each outcome. The test set was chosen to represent the entire population. The validation set was chosen to evaluate the network performance.

**Step 2:** Select input measurements

After transforming the database, the training set is submitted to the networks. Using **Model A**, (see Fig.6.2) data is submitted to the network all at once. **Model B** (see Fig.6.3) compartmentalises data into three years (i.e. 1994, 1995, and 1996) in a manner that resembles the way analysts evaluate corporate performance. **Model B** uses inter-connected neural sub-networks. The total input variables used are presented in Table 6.1 below. These variables had been discussed previously in Chapter 4. However, they are repeated here for completeness.

| Networks | Variables | 1994 | 1995 | 1996 |
|---|---|---|---|---|
| Balance Sheet | 10 | X | X | X |
| Profit and Loss | 8 | X | X | X |
| Cash Flow | 10 | X | X | X |
| Financial Summary | 6 | X | X | X |
| Key Financial Ratios | 20 | X | X | X |
| Political and Economic | 4 | X | X | X |

**Table 6.1 Facets of Failure or Success and Input Variables used**

Each facet in Table 6.1 represents a network within a sub-network and all forward pass to the first hidden layer. The first and second hidden layers are fully connected.

**Step 3:** Select Network Parameters

Table 6.2 lists the network parameters. These parameters were interchangeably used. Their use is not rigid but problem-specific and adaptability.

Network Parameters

| | |
|---|---|
| Transfer functions: | Sigmoid<br>Hyperbolic tangent<br>Linear |
| Learning rules: | Delta rule<br>Cumulative delta rule<br>Normalised cumulative delta rule |
| Topology | Number of hidden layers<br>Number of processing elements per layer<br>Functional link layers<br>Connection to prior layers |
| Learning rates: | Learning rates for each layer |

**Table 6.2 Parameters for Back-Propagation Networks**

**Step 4:** Select the Learning Rule

The learning procedure selected is the original learning rule developed by Rumelhart et. al., (1986). The back-propagation method of Rumelhart et. al., is a learning procedure for multilayered, feedforward neural networks. By means of this procedure, the network can learn to map a set of inputs to a set of outputs (Refenes, 1992).

**Step 5:** Select Network Architecture

As mentioned earlier, two types of neural network architecture were considered. **Model A** submits all possible data to a single network and **Model B** uses sub-networks for different facets within each year. The first architecture selected for training was **Model A**.

**Step 6:** Commence training

The training process includes network initialisation, iterations, optimisation of the epoch size and use of two fully connected hidden layers with eighteen units for both models. Training is conducted by varying the Global Learning Schedule for each separate network. Each Global Learning Schedule contains eighteen parameter values adjusted according to the state of the network. Training is stopped when the overall error is at a minimum level. The training strategy is the same for both models; however, training is stopped for either model if no improvement is anticipated.

**Step 7:** Test the network

The testing phase is the procedure of submitting the test and validation sets to the network in order to evaluate performance. The output neuron values will determine whether more training is needed or not. If the testing procedure identifies significant errors in the neural network, the training process should be debugged. Several factors should be examined: the training cases for quality, representativeness, and accuracy; constants within the learning algorithm; neural network node characteristics, architecture and connectivity. The neural network optimisation and generalisation metric has already been elucidated in Chapter 5.

## 6.4 The Models

As mentioned earlier, this study evaluated two types of back-propagation neural networks in the experiments: the fully connected feed-forward neural network and the time dependent structured (inter-connected) neural network.

### 6.4.1 Model A

**Model A** is the fully connected network with one input layer (174 units), two fully connected hidden layers and one output layer. There are links between all the nodes in adjacent layers as depicted in Figure 6.2 below. There is a separate link from the input layer to the hidden nodes and from hidden nodes to the output node. Each node has a connection strength or weight, which is stored in and maintained by the node on the receiving end of the link. The output node represents the outcomes from the network.

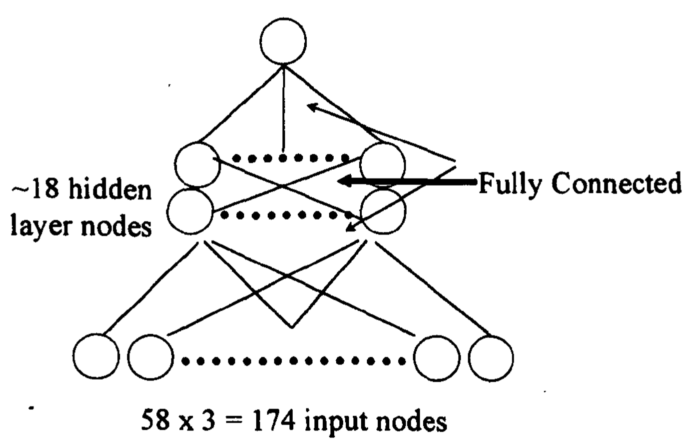



**Fig.6.2 Model A Multilayered fully connected Neural Network**

### 6.4.2 Model B

**Model B** (see Fig.6.3) is the time dependent structured (inter-connected) neural network. This model is made of a series of inter-connected sub-networks each connected to its immediate neighbours. There is a forward pass from the input layer to the first hidden layer. The first and second hidden layers are fully connected. There is a forward pass from the fully connected hidden layers to a single output layer. In order to incorporate time in the architecture, the first hidden layer in 1995 receives additional input from the previous 1994 and the first hidden of 1996 receives additional input from the previous 1995. The high level topology captures the temporal nature of the data. The low level (i.e. connection between input units to the first hidden layer) topology of the sub-networks uses domain knowledge. **Model B** (see Figure 6.3) resembles the way financial analysts evaluate corporate performance.

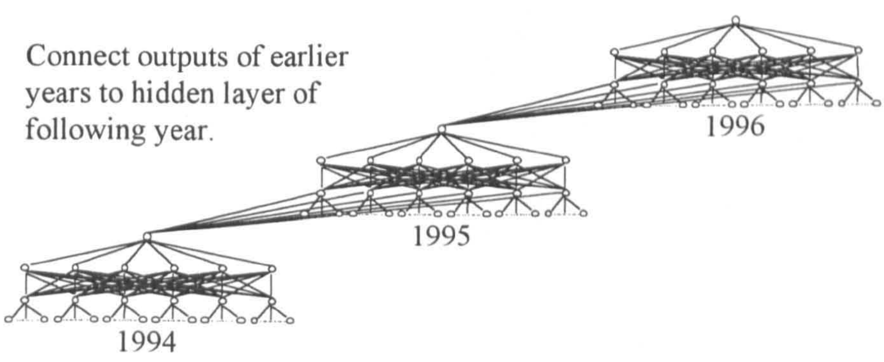



**Fig. 6.3 Inter-Connected Neural Sub-Networks**

## 6.5 Summary

This chapter has examined the software packages used to implementation the neural network approach so that the research issue can be addressed.

The NeuralWare Professional Development used to implement the study is the world's standard in professional neural network development systems. The product allows the author to build, train, refine and develop many neural network solutions. It has a menu which allows the selection from any of the major network types to create any of the 28 major paradigms. Each major class of networks has its own custom menu with options and features specific to that class. Each major network type has numerous transfer and learning functions and quadratic squashing functions. This menu allows the author to conduct various levels of training iterations. This unique facility made it possible for the research to be conducted rigorously despite the volume of the large scale employed to model the stochastic process.

# Chapter 7

# EVALUATION

## 7.1 Introduction

The implementation for the neural network approach for **Model A** and **Model B** has been reported in the previous chapter. As already stated in chapter 1, the experimental hypothesis is that the use of domain knowledge and time dependent structured neural networks can successfully discern patterns or trends in financial data and use them as early warning signals of bankruptcy conditions prevalent in currently apparently viable companies. This chapter will conduct a through evaluation of both models.

Data sources and collection have been explored in detail in Chapter 3. The data used as training, test and validation sets covers the detailed financial and descriptive information of 2,500 companies. The networks were trained on the financial, as well as, economic and political data. Financial data was obtained from The London Stock Exchange and JORDANS financial database of major British public and private companies. The London Stock Exchange sent further three CD-ROMs updates and these were received before the end of the data processing period. These updates were actually needed in order to facilitate the research. The data processing period took about 18 months to complete. Newspaper headlines were gathered using The Financial Times CD-ROM obtained from the De Montfort University Library.

The previous chapter explored neural network topologies and the reasons for selecting a particular topology. Many topologies had to be considered before selecting the preferred model. In chapter 5, a general taxonomy for the preferred model was introduced. It was decided that any architecture that processes time-varying patterns requires two distinct components: a short term memory that holds on to relevant past information (events) and an associator that uses the short term memory to classify or predict.

This chapter considers **Model A** and **Model B** for training and testing as presented in Chapter 6. The first architecture is the fully connected neural network with 174 input variables (see Fig. 6.2) where domain knowledge was not used to organise data in the neural network in any particular way. This architecture, represents most of the application development in this area to date (Husmeier and Taylor, 1997). The second architecture, is the model that incorporates time. Domain expert knowledge was used to organise data in the networks that resembles the practice of corporate financial analysts when evaluating the financial performance of the particular company.

The organisation of this chapter proceeds as follows: Section 7.2 presents evaluation criteria. Results and analysis of the models are discussed in Section 7.3. Summary and conclusions are discussed in Section 7.4.

## 7.2 Evaluation Criteria

This section describes evaluation criteria. Generalisation is the term used to refer to the ability of neural networks to produce the correct response when tested on unseen data sets. It has been shown (Odom and Sharda, 1990) that to achieve significant levels of predictive validity, the proportion of correct positive predictions (classifications of bankrupt and non-bankrupt for example) in both cases should exceed the base rate of 50 percent. Wilson and Sharda, (1996) suggest that in order to distinguish between a "good" and a "bad" network a more stringent threshold of 5% and 95% should be considered. This study adopted the stringent criteria.

### 7.2.1 What is a good Network?

A good network is a model that generalises very well from unseen data sets (Moody, 1992). A bad network is a model that simply memorises the training data set and performs badly when tested against unseen data sets (Lawrence et. al., 1997). Whether a network is good or bad is judged against a well-defined testing threshold. For instance, consider a popular testing threshold of 50:50. If one output neuron exceeded 50% (and the other neuron's value was ≤ 50%), the network classified the case as the corresponding group associated with the first group. The above testing threshold is not a good judgement of whether a network is good or bad since the network will simply push its scale of predictions to the middle without a clear-cut polarisation. Although the distinction between a "bad" and a "good" network depends on the testing criteria used, the complexity of the problem will determine the appropriate testing thresholds. The more stringent the testing threshold, the more reliable the network (Watrous, 1987). Table 7.1 shows some examples for correct and incorrect classifications. Table 7.1 illustrates how testing thresholds are applied to neural networks outputs. What is shown in Table 6.3 are the results obtained by the author from a simple network with a small data sample as reported by Nasir et. al., (2000).

The Profit and Loss Account (Sub-Network)
Neural Network Trained on 82 companies.
Neural Network Results for Test Set of 18 companies.

| Desired **Output** | Output **Neuron** | Threshold **0.10&0.90** | Threshold **0.05&0.95** | Wrongly **Classified** |
|---|---|---|---|---|
| 0.000000 | 0.000302 | correct | correct | NO |
| 0.000000 | 0.002979 | correct | correct | NO |
| 1.000000 | 1.013013 | correct | correct | NO |
| 0.000000 | 0.027065 | correct | correct | NO |
| 1.000000 | 0.926811 | correct | don't know | NO |
| 0.000000 | 0.119913 | don't know | don't know | NO |
| 0.000000 | 0.091476 | correct | don't know | NO |
| 0.000000 | 0.020659 | correct | correct | NO |
| 0.000000 | 0.121272 | don't know | don't know | NO |
| 0.000000 | 0.120976 | don't know | don't know | NO |
| 1.000000 | 0.975621 | correct | correct | NO |
| 1.000000 | 0.990373 | correct | correct | NO |
| 0.000000 | 0.003497 | correct | correct | NO |
| 0.000000 | 0.070214 | correct | don't know | NO |
| 0.000000 | 0.013654 | don't know | don't know | NO |
| 0.000000 | 0.002433 | correct | correct | NO |
| 0.000000 | 0.052159 | correct | correct | NO |
| 0.000000 | 0.065421 | correct | don't know | NO |

**Table 7.1 Simple Model Neural Network Results**

Looking at the above results, there were no wrong classifications, however, the network returned some companies as "don't knows" depending upon testing threshold.

### 7.2.2 Training Error Measurement

It has always been assumed that training should stop when the Root Mean Square Error (RMSE) is considered low (Mozer, 1993). However, RMSE is not always the best measure of how well a network has learned (Taylor and Lisboa, 1997). It is possible to achieve an RMSE of 0.01 for example, but if the average change from one time step to the next is the same, then a great deal has not been achieved (Bose and Liang, 1996). Properly defining target error limits is one way of guarding against such a problem. In this way, the task becomes one of categorisation and error magnitude takes a different meaning. What had been done in the study is to submit the test set to the network at the end of each run irrespective of whether the RMSE was low or high. This proved very useful.

## 7.3 Results of Model A

The results of the experiments for **Model A** and **Model B** are presented in this section. As already stated, the results of runs generated represent training cases for 2,500 companies selected randomly from a population of 270,000.

### 7.3.1 Model A

The experimental results of the first run and its parameter values are shown below. Applying the evaluation criteria as discussed in section 7.2, the generalisation performance of the network is disappointing. When evaluating the predictive capability of the network, four testing thresholds (0.5:0.5, 0.20:0.80, 0.10:0.90, and 0.05: 0.95) were used. These testing thresholds identify how stringent the allowable variation in output neurons can be when predicting the status of the companies in the training set. This basis was used for correct and incorrect classifications. When checking the output neuron value, the network simply pushes its scale of predictions to the middle without a clear-cut deviation from the average. Using the 50:50 threshold for example, the network performance did not satisfy our defined criteria. The network's predictions were all centred in the middle without a clear-cut polarisation. However, when using the stringent criteria (0.05:0.95), the network achieved 8%

correct classification for the bankrupt and 11% classification for the non-bankrupt companies. Therefore, over 90% of the both cases were returned as "don't knows".

| | |
|---|---|
| RUN NO: | FC1 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Sigmoid |
| LEARNING RULE | Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| Parameters | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Rate | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 10 | 10 | 10 | 10 | 10 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 40 | % healthy wrong | 60 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 88 | % bankrupt wrong | 2 | % bankrupt don't know | 10 |
| % Healthy right | 23 | % healthy wrong | 53 | % healthy don't know | 24 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 22 | % bankrupt wrong | 1 | % bankrupt don't know | 77 |
| % Healthy right | 17 | % healthy wrong | 23 | % healthy don't know | 60 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 8 | % bankrupt wrong | 1 | % bankrupt don't know | 92 |
| % Healthy right | 11 | % healthy wrong | 7 | % healthy don't know | 82 |

What follows is the description of the methods used in trying to improve the above results (see Section 7.3.1.1).

#### 7.3.1.1 Improving the Network

The author applied each of the following possible approaches in an attempt to improve upon the results obtained so far from **Model A.** Each of the possible approaches is considered separately and it is applied to the model to see whether better results can be possible and if not, the author reports his findings at the end of each possible approach.

Lapedes and Farber (1988) suggested that where convergence cannot be obtained, the first work is to check the particular network for surplus processing units (inputs). They argue that the aim of this exercise is to find out whether there are some units that are deemed, in some sense, redundant. If however some units are found redundant, they should be removed. A unit is redundant if it carries a zero weight in comparison to other units in the network (Silva and Amelda, 1990). The author looked for redundant units however none is reported. Having said that, the aim of the study is to force the network to learn with the variables (see Table 4.1) selected using domain expert knowledge. The network did not return any of the variables selected as redundant.

Mozer and Smolensky (1990) identified a "skeletonisation" technique as a way of improving back-propagation learning. The observation behind this technique is that after training, units vary in their functional importance for solving the problem at hand. It was argued that a network with a smaller number of units might have fared as well as or even better than the network under consideration. Mozer and Smolensky suggested that a good way of discovering whether a unit is functionally important is to monitor what happen if the unit and its connections are removed. The relevance of a unit can then be defined in terms of the difference in the network's performance when the unit is included as compared to when the unit is removed. If this discrepancy is large then the unit is deemed functionally useful and it should be retained. However, if the discrepancy is small, then the unit's usefulness is questionable and it may be removed.

Although convergence problems abound in deciding a critical level of relevance, Mozer and Smolensky side-step this issue by sketching the skeletonisation technique as follows.

Step (a) train a fully connected network to a level where an acceptable level of error is produced for every training pattern.
Step (b) compute the relevance for each unit in the network.
Step (c) eliminate from the network the unit with the smallest relevance value.
Repeat Steps (a)-(c) a set number of times and halt at a pre-determined stopping point.

The main concern with this approach is that the input units responsible for processing the exception may be removed. The upshot of this would have been a smaller network, but one which no longer solves the original problem at hand. This appears to point to a rather profound problem with the method. Mozer and Smolensky appear to have introduced a reasonably principled means for "pruning" units automatically, they have failed to provide any guidelines for when to halt the procedure. There are further grounds for concern. The approach of Mozer and Smolensky would risk overfitting the data. When this is the case, the network will become less effective in generalisation. The main objective of the study is to model a network with enough power to provide a good fit to the data, generalise very well from a large data sample, but not so much power that it risks overfitting. Domain knowledge had been used to select those financial variables that are deemed relevant in order to solve the problem at hand, pruning strategies as suggested by Mozer and Smolensky if applied to the study *would ultimately exclude variables that should be included.* This method is not satisfactory.

Hirose et. al. (1991) proposed using optimal number of hidden nodes in the network. The issues concerning optimal number of hidden units was tested by varying the number of hidden nodes between neural network runs as shown in the Global Learning Schedule (see Appendix B). For each run, the network was trained on the same examples. Each was trained towards convergence but some networks did not converge at all. Some networks did converge but performed poorly when tested against test set. The author's expectations was based on the consistent theories of neural networks that convergence can be attained when the derivatives of the error with respect to each weight became zero. This had been the author's expectation but did not know when this would occur. This did not occur when the author applied the work of Hilrose et. al. to the study. Therefore, approaches that require training to convergence with huge samples are therefore problematical (Frean, 1989).

Applying what has been described so far, 10 network runs were conducted (see Appendix B). The results obtained remained very unsatisfactory and quite disappointing. It was decided to continue the network runs, hoping that further improvements would be achieved later. Training neural networks is a trial and error process and it is difficult to known in advance when convergence would occur.

The work of Ooyen and Nienhus, (1992) was examined rigorously. They proposed a modification to the backpropagation method in a manner slightly different from the work of Mozer and Smolensky. The modification consists of a simple change in the total error-of-performance function that is to be minimised by the algorithm. It was suggested that learning would improve and thus promote convergence. The study experimented with runs starting from different initialisations of the network. The same initialisations were used for both the modified method as suggested and the original method with no modifications to the error function. When adopting this approach to solve the problem at hand, problems abound however. Although, in principle, the suggestion appears to be self-limiting, no conditions on when to stop training were discussed or examined. In using this approach, it became clear that as the network goes through its learning process, it goes through stages in which the improvement of the response is extremely slow. It was noted later that this delay of the convergence is caused by the derivative of the activation function. These periods of stagnation became longer than expected and training was abandoned because the network suddenly goes into local minima. Trying to force the network out of its present state would almost certainly produce further errors due to the derivatives of the activation function. Attempting to solve this would mean examining the derivatives *seriatim* one by one. This would be tedious and time consuming.

Perhaps the most well known approach of improving a back-propagation network is that described by Fahlman and Lebiere (1990) and Fahlman, (1992). They proposed that the initial network should contain a set of input units, a set of output units and interconnections between the input and output units with no hidden layers. The single layered network should be trained until performance was within some pre-defined criterion. Typically, the network would be trained with certain number of epochs. For each epoch, the set of input patterns should be different. This should be repeated a number of times until convergence was achieved and then the network performance is assessed. If the network was now performing within an acceptable limit, training should cease. However, if the network's performance was not judged acceptable, then a hidden layer "candidate" unit should be introduced. Fahlman and Lebiere (1990) demonstrated that this method results in faster learning times and that it eventuates in small networks that generalise very well. They claimed that the faster learning times, in part, arose from the process of freezing the weights and only training one hidden layer of connection at a time. When trying this approach, two problems became apparent. First, this is a cascade-correlation method where there is no backward propagation of an error signal through intermediate layers of hidden units; only one layer of connections is trained for each step in the algorithm. This supports the reason why learning times are shortened considerably. Second, generalisation ability can critically depend on the problem under consideration. It is considered that bankruptcy prediction is learning about 'logical' rather than 'natural' problems. Logical means making a judgement from observed dependent and independent variables. Natural problems are purely coincidental and judgement may not necessarily follow from their observation. Consequently, the approach suggested by Fahlman and Lebiere (1990) would fare better with natural problems than in logical problems i.e. the bankruptcy phenomenon. Clearly, the implications of their arguments are important insofar as they suggests that, depending on the problem at hand, the use of large structures may or may not be desirable. Nevertheless, it will suffice to say that, until more work addresses this particular issue of single layered networks in much more detail, further speculation is perhaps unwarranted.

Sperduti and Starita (1993) suggested how adaptation of the steepness of the sigmoid functions during learning could improve convergence. Their adaptation method is obtained by training a standard network with fixed sigmoids and a learning rule whose main component is gradient descent with adaptive learning parameters. The basic idea here is the introduction of variation on network parameters so that the architecture can be optimised with respect to the number of units presented to the network. Optimisation of units is then obtained by introducing a tendency to decay to zero in the parameter values and comparing this with the sensitivity of the input units. In this way, according to Sperduti and Starita (1993), units that are not useful in implementing the target function can be removed. When using this approach for this study, the network was stuck in local minima for a long time. It became difficult to set the decay rate in such a way as to obtain good results without risking slowing down the convergence speed of the learning or causing all the network parameters to be null. The resulting procedure thus compromises between speed of learning, input units, and network generalisation. The approach of Sperduti and Starita (1993) was therefore not satisfactory.

The results of all the network runs produced by the author for **Model A** are shown in Table 7.2, which lists, for each trial of the network run, the various parameters for controlling the learning process. Recall that these network runs were produced as a result of looking into the works of other authors in solving difficult networks and also to see network generalisation can be achieved by carrying out many network runs. However, in this case, as more runs were carried out the results produced from the network runs were showing any improvement. The author decided to stop after carrying out 20 network runs. The results of the runs are produced in Appendix B.

| | Backpropagation | | | Classification Criteria | | | | Classification Criteria | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| No. | Learning Parameters | | | 0.50 and 0.50 | | | | 0.05 and 0.95 | | | |
| FC | Transfer Function | Learning Algorithm | Iterations | HR % | BR % | HW % | BW % | HR % | BR % | HW % | BW % |
| 1 | Sigmoid | Delta | 50000 | 40 | 96 | 60 | 4 | 11 | 8 | 7 | 1 |
| 2 | Sigmoid | Delta | 75000 | 92 | 94 | 8 | 6 | 64 | 7 | 1 | 1 |
| 3 | Sigmoid | Delta | 250000 | 37 | 96 | 63 | 4 | 11 | 8 | 8 | 1 |
| 4 | Linear | Delta | 50000 | 36 | 96 | 64 | 4 | 8 | 8 | 9 | 1 |
| 5 | Linear | Delta | 150000 | 36 | 96 | 64 | 4 | 9 | 8 | 9 | 1 |
| 6 | Sigmoid | CumDelta | 50000 | 34 | 96 | 66 | 4 | 7 | 8 | 9 | 1 |
| 7 | TanH | Delta | 50000 | 50 | 96 | 50 | 3 | 3 | 19 | 1 | 0 |
| 8 | Sigmoid | NormDel. | 50000 | 51 | 96 | 49 | 3 | 4 | 19 | 1 | 0 |
| 9 | Linear | Delta | 200000 | 52 | 96 | 48 | 3 | 16 | 19 | 1 | 0 |
| 10 | Sigmoid | Delta | 50000 | 42 | 98 | 58 | 2 | 4 | 9 | 9 | 0 |
| 11 | Sigmoid | Delta | 50000 | 38 | 98 | 62 | 2 | 4 | 9 | 14 | 0 |
| 12 | TanH | CumDelta | 50000 | 40 | 98 | 60 | 2 | 4 | 9 | 11 | 0 |
| 13 | Sigmoid | Delta | 50000 | 40 | 97 | 60 | 3 | 4 | 10 | 11 | 0 |
| 14 | Sigmoid | Delta | 300000 | 41 | 97 | 59 | 3 | 4 | 11 | 11 | 0 |
| 15 | Sigmoid | Delta | 50000 | 48 | 96 | 52 | 4 | 3 | 14 | 3 | 0 |
| 16 | Sigmoid | Ext.BPB | 50000 | 49 | 96 | 52 | 4 | 4 | 14 | 3 | 0 |
| 17 | Linear | Delta | 50000 | 51 | 96 | 49 | 4 | 6 | 15 | 3 | 0 |
| 18 | Sigmoid | TanH | 50000 | 52 | 96 | 48 | 4 | 7 | 15 | 3 | 0 |
| 19 | Sigmoid | Delta | 150000 | 50 | 95 | 50 | 5 | 6 | 15 | 6 | 1 |
| 20 | TanH | Delta | 50000 | 44 | 95 | 56 | 5 | 14 | 15 | 12 | 1 |

**Table 7.2 Results of network runs for Model A**

**Key:**

**HR** Healthy Right

**HW** Healthy Wrong

**BR** Bankrupt Right

**BW** Bankrupt Wrong

From the above results of this experiment, it is apparent for the bankruptcy prediction problem that, **Model A** had clearly not worked.

The best results produced by **Model A** (see Section 7.3.1.2) show that the network centres its scale of predictions to the middle without clear-cut deviations from the average. Two reasons can be advanced for this lack of generalisation. Firstly, the network (**Model A**) carried too many weights and became too powerful but less effective. When this is the case, the network will memorise the training set but be less effective in generalisation. Secondly, fully connected networks will do well where small samples are involved and this had been the case with work reported by numerous researchers as explained in Chapter 3. The author's expectation now is that better prediction can be obtained with a structure based on domain knowledge. This explains the reason why alternative architecture is considered in this thesis. Before the author presents his work using alternative architecture, Model A's best results is presented in Section 7.3.1.2 below.

#### 7.3.1.2 Model A Best Solution

From the results of the whole experiment for this model, it is apparent that for bankruptcy prediction problem, Run FC2 offer the best solution. Results from Run FC2 are produced below.

| | |
|---|---|
| RUN NO: | FC2 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Sigmoid |
| LEARNING RULE | Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 175000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 35000 | 20000 | 35000 | 40000 | 45000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 6 | % bankrupt don't know | 0 |
| % Healthy right | 92 | % healthy wrong | 8 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 86 | % bankrupt wrong | 4 | % bankrupt don't know | 10 |
| % Healthy right | 76 | % healthy wrong | 1 | % healthy don't know | 23 |

Classification Criteria 0.10 and 0.90

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 21 | % bankrupt wrong | 3 | % bankrupt don't know | 76 |
| % Healthy right | 69 | % healthy wrong | 1 | % healthy don't know | 30 |

Classification Criteria 0.05 and 0.95

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 7 | % bankrupt wrong | 1 | % bankrupt don't know | 92 |
| % Healthy right | 64 | % healthy wrong | 1 | % healthy don't know | 35 |

Using the preferred (stringent) criteria (i.e. 5% and 95%), the network returned 92% of bankrupt and 34% of non-bankrupt cases as 'don't knows'. However, it predicted correctly, 7% of bankrupt and 64% of non-bankrupt cases, and misclassified 1% in both cases. As mentioned in Chapter 5, it is not possible to know in advance which topology would work for a particular problem, however, different architectures should be tried until the appropriate architecture can be found if at all possible.

Finally, the reason for trying **Model A** is that neural networks are meant to be able to work with any data and in effect the structure emerges in the strength of the weights. The research hypothesis was that this would not be enough – that a large network would not be able to learn and generalise from data without some structure based on domain knowledge. Section 7.3.2 introduces an alternative architecture.

### 7.3.2 Model B

The alternative architecture proposed will be the time dependent structured (inter-connected) neural network. This is shown in Fig. 6.3 in Chapter 6.

#### 7.3.2.1 Why Propose an Alternative Architecture?

The reason for considering an alternative solution is consistent with the theories of neural networks. The first architecture (the fully connected network) had clearly not produced an optimal solution. As stated earlier, the context of the problem is that there are no fixed rules in determining the network structure or its parameter values, a large number of network topologies may have to be constructed with different structures before determining the acceptable model. The trial-and-error process can be tedious, and the experience of the developer can be invaluable in the search for a good model.

#### 7.3.2.2 Why Inter-Connected Neural Sub-Networks?

Although the following reasons have been stated in Chapter 5, they are repeated here for completeness and clarity. A time dependent structured neural network was considered because:

- it allows the use of domain knowledge
- it has fewer weights as opposed to the fully connected network
- it allows interconnectedness in the hidden layer
- its high level topology captures the temporal nature of the data
- it allows connection of earlier years to the hidden layer of the following year
- it resembles the way financial analysts evaluate corporate performance
- it tends to remove some of the limitations of single point predictions as reported in Husmeir and Taylor (1997)
- it allows complex relationships between input parameters, network parameters, and the forecast period to be captured effectively.

#### 7.3.2.3 Results from Model B

For **Model B,** 64 runs (running the model with different parameters) were performed with different random initial weights. The reason for these large runs was that every other run shows some improvement. So, it was decided to continue the runs until an optimal solution was achieved. The results of the first run will now be presented.

| | |
|---|---|
| RUN NO: | NPR1 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Sigmoid |
| LEARNING RULE | Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 75 | % bankrupt wrong | 25 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 65 | % bankrupt wrong | 15 | % bankrupt don't know | 20 |
| % Healthy right | 91 | % healthy wrong | 4 | % healthy don't know | 5 |

Classification Criteria 0.10 and 0.90

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 54 | % bankrupt wrong | 13 | % bankrupt don't know | 33 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 10 |

Classification Criteria 0.05 and 0.95

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 38 | % bankrupt wrong | 11 | % bankrupt don't know | 51 |
| % Healthy right | 86 | % healthy wrong | 1 | % healthy don't know | 13 |

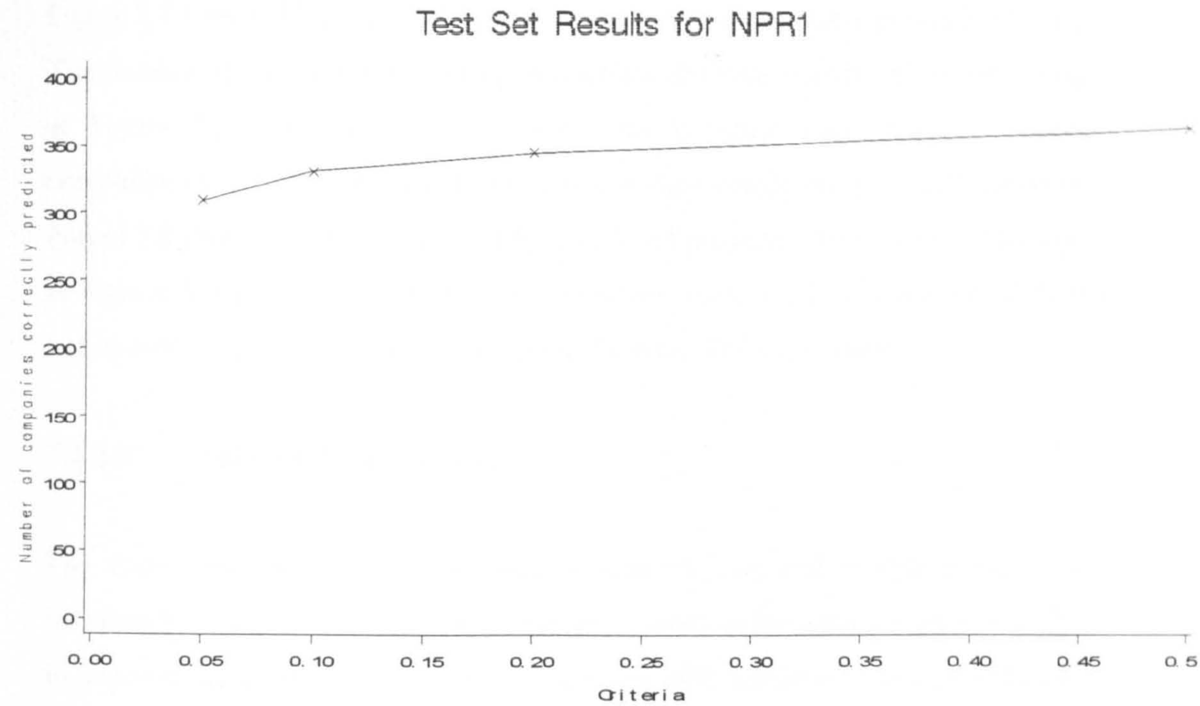



**Figure 7.1 Model B Run NPR1 performance based on our criteria**

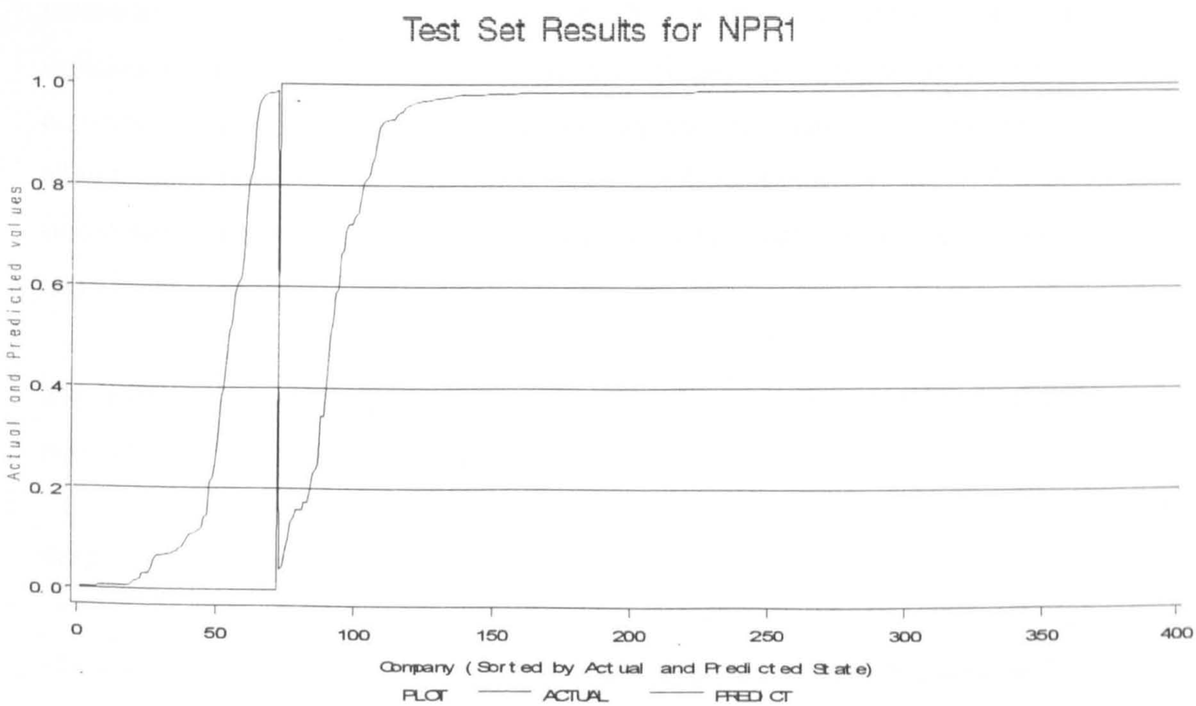



**Figure 7.2 Model B NPR1 network performance**

Figure 7.1 shows the correct predictions according to the author's pre-defined criteria. The number of companies correctly predicted for different criteria. However, looking at Figure 7.2, the first glitch represents the bankrupt cases (i.e. 72 bankrupt companies) and the second glitch represents healthy companies (i.e. 328 companies). Figure 7.2 shows company predicted by actual and predicted state. The results shown in Figures 7.1 and 7.2 are encouraging; however, more work was performed further out in order to improve the results obtained from the first experiment.

#### 7.3.2.4 Network Improvement

The above network shows high cases of don't knows and a high proportion of misclassifications. So, efforts had to be made to improve the network. Previous efforts to improve the generalisation performance of the fully connected network (**Model A**) differ from the inter-connected network approach in a fundamental way. The organisation of data alone in the inter-connected network is sufficient to determine the parameters and their relationships. Although in both cases, the training data is sufficiently large (2,500 companies), the task in general with the inter-connected network is rather more complex. Having said that, the time dependent approach, allows the network, and its parameters, to be constrained in a way that is known to reflect the properties of the task that it is to perform. What follows are the possible steps taken to achieve convergence.

The following is a step by step description of the methods applied to the above network in order to improve its results.

**Step 1:** Network pruning.

The study considered the *two stage pruning technique* described by Sietsma and Dow (1991). The first stage is to determine hidden units with outputs close to zero for all input patterns and remove them. The second stage is more drastic. It was suggested that all the hidden units with the same outputs for all training patterns should be removed. If this procedure meant that the entire layer is removed, then reconnect and try again. Without reducing the number of input units in the network, the author firstly check those hidden units with output close to zero as suggested by Sietsma and Dow. However, none of the hidden units output value is close to zero. The author did not try the second approach because none of the hidden units in the network carries the same output value for all training patterns.

**Step 2:** Examine network connections rigorously.

To examine the connections from the input layer, it is necessary to look at each of the processing elements that the input layer is connected to. This was done using a Hinton diagram. The author checked for irregularity and inconsistencies on every single weight that is linked to each network connection. This had to be done because parameters value inconsistency can cause all weights on the network connection to be null (Fahlman and Lebiere,1990).

**Step 3:** Jog weights on the connections.

Jogging weights for all connections helps to force the network out of its current state. The current state of the network could be poor performance or local minima (Baldi and Hornik, 1989). Jogging causes the network to be active again and ready for re-training (Ash, 1989). This study used the Gaussian distribution to set the high and low weight limits within +/-1 sigma. Using this interval helps to identify those weights that need to be pruned. This approach attempts to minimise network complexity while enabling the author to retain the original input units to the network.

**Step 4:** Increase training iterations

Training counts were randomly increased or decreased between runs. Although the choice of training counts depends on the nature of data, size of data and network parameters. Some improvements were noticed on the network performance by simply varying the training iterations.

**Step 5:** Switch between transfer functions

The choice of a transfer function is determined by the nature of the data and what the network is trying to learn (Trippi and Turban, 1996). The important observation in this study was to switch between transfer functions and learning rules at different runs. Trippi and Turban (1996) suggest that if the problem involves learning about clear cut "deviations" from the average, hyperbolic tangent works best. For example, Odom and Sharda (1990) have compared the prediction capabilities of the sigmoid transfer function with the hyperbolic tangent. Using a training set of 83 bankrupt companies, the network was able to predict with an accuracy of 56.78 percent when employing the hyperbolic tangent. This was opposed to poor generalisation when employing the sigmoid transfer function. According to Trippi and Turban (1996), if the problem involves learning about "average" behaviour the sigmoid transfer function works best (see Section 6.5.1.2). Weigend and Gershenfeld (1993) suggest that if the objective is to learn to pick out "exceptional" situations, the hyperbolic tangent performs better. The author applied this approach by switching between alternative transfer functions and find significant improvement in the results obtained. Therefore the approach suggested Trippi and Turban was very helpful to the study. From this point onwards, the author decided to fix the transfer function at the hyperbolic tangent (TanH) and the learning rule at the Cumulative Delta Bar. However, the appropriate level of network parameterisation must still be established. The author continued to find the right parameter values. Recall this can only be achieved only by trial and error process. There is no hard and fast rule about this important procedure.

**Step 6:** Revisit network development issues and network parameters

Many parameters and decisions that were involved in developing the networks in this study had to be revisited again. Recall that both transfer functions and learning rules are now firmly established. The author now presents all the extensive (not exhaustive) review conducted and these reviews can be found in Table 7.3 below.

- Check the number of training and test sets.
- Confirm the training and test sets.
- Confirm method of transferring data into suitable input values.
- Determine the number of hidden layers.
- Check the pattern of connectivity again.
- Revisit the network size:
  a) Check the number of processing units (PE) in the hidden layer.
  b) Check the number of processing units (PE) in the hidden layers.
  c) Check the number of processing units (PE) in the output layer.
- Determine the initial input weights.
- Select a propagation rule.
- Select an activation rule.
- Select a transfer function.
- Select a learning rule.
- Determine the learning parameters.
- Select diagnostic rule.
- Commence training again.

**Table 7.3 Network parameters and decisions review procedure.**

After carrying out all the above extensive reviews, optimal generalisation was not achieved. However, the results obtained are produced below.

| | |
|---|---|
| RUN NO: | NPR27 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | TanH |
| LEARNING RULE | Norm-Cum-Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 1000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 83 | % healthy wrong | 17 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 85 | % bankrupt wrong | 2 | % bankrupt don't know | 13 |
| % Healthy right | 59 | % healthy wrong | 6 | % healthy don't know | 35 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 77 | % bankrupt wrong | 2 | % bankrupt don't know | 21 |
| % Healthy right | 49 | % healthy wrong | 3 | % healthy don't know | 48 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 66 | % bankrupt wrong | 2 | % bankrupt don't know | 32 |
| % Healthy right | 37 | % healthy wrong | 2 | % healthy don't know | 61 |

The results shown above indicate that more work had to be done in order to improve upon the results obtained from NPR27. For classification networks, the search for optimal solution can be slow and unstable. However, the search can be greatly improved by using the strategies employed previously by other researchers. The author will now present his search for optimal solution by looking into the works of other researchers.

The author checked the network for overfitting. According to Jones (1990) all standard neural network architectures should be checked for overfitting since they are prone to overfitting. There are two ways to check whether the above network may have overfitted the training data. First, the number of dimensions of the parameter space must be checked for irregularity. Second, the effective size of each dimension is also checked for irregularity. Weigend et. al., (1991) and Moody, (1992) suggest regularisation, such as weight decay as a method of treating overfitting. It is difficult to see how in this study, the above network could have overfitted due to the scale of dataset used for training. However, it was perhaps proper to check for possible overfitting anyway.

The author examined the issue of hidden units in the layer once more. Neural networks are flexible tools for time series processing and pattern recognition and optimal solution can be obtained if the appropriate number of hidden units is used. It was suggested by Jacobs, (1988) and Ash, (1989) that by increasing the number of hidden neurons in a 2-layer architecture any target function can be approximated arbitrarily close. The author tried this experiment by changing the number of hidden units arbitrarily as part of the trial and error process. The author then tested the performance of the network and found some slight improvement in the results produced as indicated in NPR28-35 (see Section 7.3.2.6). Recall that the author is dealing with a chaotic time series prediction and the goal is to predict three steps ahead based on previous observations. This implies that a large number of networks runs must be carried out in the search for optimal solution.

One of the major problems with feed-forward network learning remains the accuracy and speed of learning algorithms. Since the learning problem is a complex and highly nonlinear one (Cater, 1987), iterative learning procedures must be used to solve the optimisation problem. Casdagli (1989) argues that chaotic time series prediction requires long learning iterations to find an optimum. The author therefore decided to increase the number of training iteration in each network run with fixed parameter values. However, it was noticed that increasing the level of training iteration in each network alone will not provide optimum solution unless the right parameter values is assigned to each level of training iteration. Bose and Liang (1996) asserted that it is possible to use different learning parameters for various level of training iteration. He showed how to set the level of training iteration and the right parameter values so that each level reach their best performance. The author tried this approach and found significant improvement in the performance of the network (see NPR 36-51).

An important technique used by the author in this investigation to find optimum solution is to control the use of bias node. The author connected the bias to every layer in the network; however, no significance improvement in performance was noticeable. Then, the bias node was de-selected and investigated further. The internal units of the bias node were incrementally changed between runs to find the right balance. A constructive technique was employed to sequence the internal units of the bias node; the weights were also adjusted accordingly at each subsequent run. After completing this internal adjustment, the bias node was then reconnected to the output layer. This experiment was successful as indicated between NPR52-61.

After all the above improvements had been implemented, the network training iteration increased or decreased as appropriate, selecting the right transfer function and learning rules, the best solution obtained is presented in Section 6.5.2.5 below.

#### 7.3.2.5 Model B Best Solution

This subsection presents the best results for **Model B**. The remaining results of runs for this model can be found in Appendix C. Although sixty-four network runs have been reported in the appendix, two subsequent runs (65 and 66) are not reported since they did not improve upon the 'Best Solution Run'. After the $64^{th}$ run, the network error starts to rise again. We decided to stop and accept the results from run 64 as our best possible solution.

RUN NO: NPR64
SUMMATION FUNCTION Sum
ERROR FUNCTION Standard
NOISE Uniform
TRANSFER FUNCTION TanH
LEARNING RULE Norm-Cum-Delta
EPOCH SIZE 16
ITERATIONS 1000000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 200000 | 20000 | 200000 | 200000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

No of Bankrupt 72
No of Healthy 328

% Bankrupt right 96 % bankrupt wrong 4 % bankrupt don't know 0
% Healthy right 97 % healthy wrong 3 % healthy don't know 0

Classification Criteria 0.20 and 0.80

No of Bankrupt 72
No of Healthy 328

% Bankrupt right 94 % bankrupt wrong 3 % bankrupt don't know 3
% Healthy right 96 % healthy wrong 3 % healthy don't know 1

Classification Criteria 0.10 and 0.90

No of Bankrupt 72
No of Healthy 328

% Bankrupt right 90 % bankrupt wrong 3 % bankrupt don't know 7

| | | | | | |
|---|---|---|---|---|---|
| % Healthy right | 96 | % healthy wrong | 1 | % healthy don't know | 3 |

Classification Criteria 0.05 and 0.95

| | | |
|---|---|---|
| No of Bankrupt | 72 | |
| No of Healthy | | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 91 | % healthy wrong | 1 | % healthy don't know | 8 |

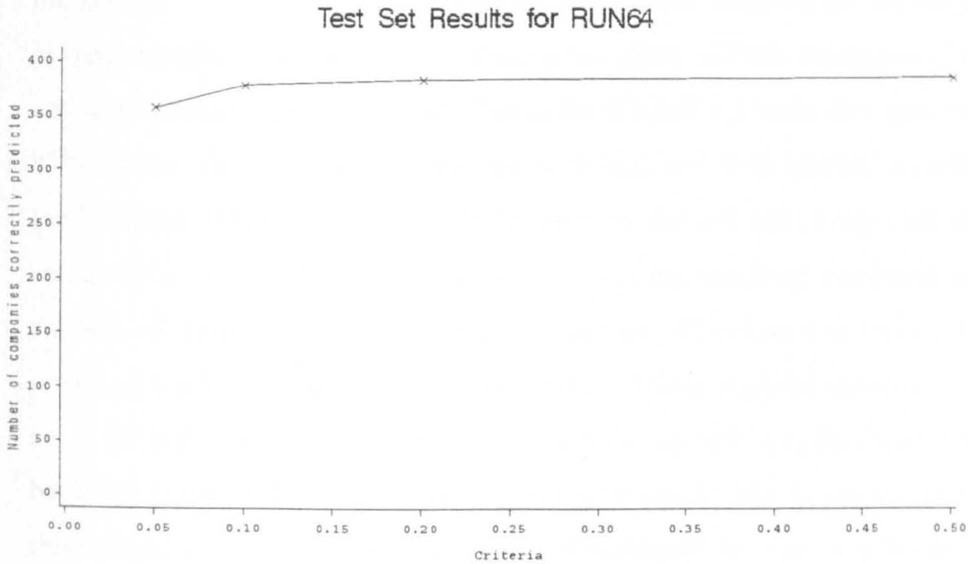



**Figure 7.3 Model B Run NPR64 performance based on our criteria**

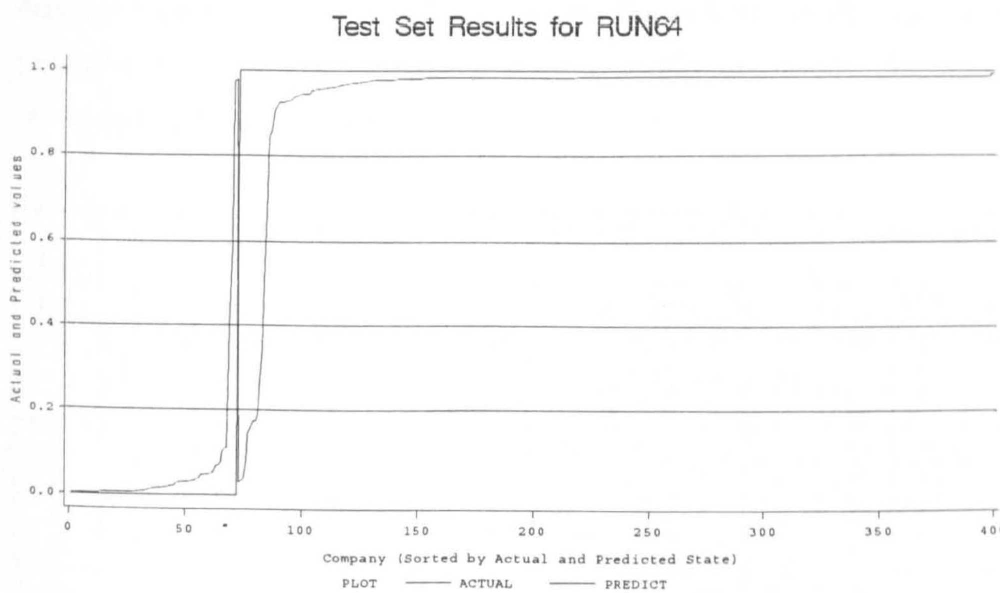



**Figure 7.4 Model B Run NPR64 network performance**

### 7.3.2.6 Discussion of Results

The input units in the above network represented data values for various financial, economic and political measurements as detailed in Table 4.1 (see Chapter 4). When checking the output neuron values for the above network, the prediction results were very promising. Two testing thresholds will be used to test the predictive capability of the network. These testing thresholds determine how stringent the allowable variation in output neurons can be when predicting the status of both categories (i.e. bankrupt and non-bankrupt) in the test set. Using the 0.5 and 0.5 basis, the network achieved 97% correct classifications for the non-bankrupt, and 96% correct classifications for the bankrupt companies. Although the network did not return any company in both categories as 'don't know', it misclassified 3% of non-bankrupt companies as bankrupt and 4% of bankrupt companies as non-bankrupt. The former is known as a type 1 error and the latter is known as a type 2 error. Using criteria that are more stringent; i.e. 0.05 and 0.95, the network achieved 91% correct classifications for the non-bankrupt companies and 85% correct classifications for the bankrupt companies. For this criterion, the network did return 8% of non-bankrupt and 13% of bankrupt cases as 'don't knows'. It misclassified 1% of non-bankrupt companies as bankrupt and 3% of bankrupt companies as non-bankrupt. The summary results are schematically depicted Figures 7.3 and 7.4. Table 7.3 lists, for each trial of the run, the various parameters for controlling the learning process. In this run, 64 trials were carried out of which details are in Appendix C.

| Run | Backpropagation | | | Classification Criteria | | | | Classification Criteria | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| No. | Learning Parameters | | | 0.50 and 0.50 | | | | 0.05 and 0.95 | | | |
| FC | Transfer Function | Learning Algorithm | Iterations | HR % | BR % | HW % | BW % | HR % | BR % | HW % | BW % |
| 1 | Sigmoid | Delta | 50000 | 95 | 75 | 5 | 25 | 86 | 11 | 1 | 13 |
| 2 | Sigmoid | Delta | 75000 | 95 | 78 | 5 | 22 | 87 | 44 | 1 | 10 |
| 3 | Sigmoid | Delta | 250000 | 95 | 82 | 5 | 18 | 87 | 51 | 0 | 11 |
| 4 | Linear | Delta | 50000 | 95 | 92 | 5 | 8 | 87 | 66 | 1 | 6 |
| 5 | Linear | Delta | 150000 | 95 | 93 | 5 | 7 | 87 | 72 | 1 | 6 |
| 6 | Sigmoid | CumDelta | 50000 | 97 | 13 | 3 | 87 | 8 | 7 | 1 | 2 |
| 7 | TanH | Delta | 50000 | 95 | 75 | 5 | 25 | 87 | 39 | 1 | 11 |
| 8 | Sigmoid | NormDel. | 50000 | 97 | 19 | 3 | 81 | 0 | 0 | 0 | 0 |
| 9 | Linear | Delta | 200000 | 72 | 93 | 28 | 7 | 20 | 62 | 1 | 2 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 10 | Sigmoid | Delta | 50000 | 71 | 93 | 26 | 7 | 23 | 63 | 1 | 3 |
| 11 | Sigmoid | Delta | 50000 | 70 | 94 | 30 | 6 | 21 | 63 | 6 | 2 |
| 12 | TanH | CumDelta | 50000 | 74 | 94 | 30 | 6 | 21 | 63 | 4 | 2 |
| 13 | Sigmoid | Delta | 50000 | 72 | 94 | 28 | 6 | 21 | 64 | 3 | 2 |
| 14 | Sigmoid | Delta | 300000 | 71 | 94 | 29 | 6 | 21 | 63 | 1 | 2 |
| 15 | Sigmoid | Delta | 50000 | 71 | 94 | 29 | 6 | 24 | 63 | 1 | 21 |
| 16 | Sigmoid | Ext.BPB | 50000 | 70 | 94 | 30 | 6 | 23 | 64 | 3 | 2 |
| 17 | Linear | Delta | 50000 | 70 | 94 | 30 | 6 | 24 | 64 | 3 | 2 |
| 18 | Sigmoid | TanH | 50000 | 74 | 94 | 26 | 6 | 27 | 65 | 1 | 1 |
| 19 | Sigmoid | Delta | 150000 | 74 | 94 | 26 | 6 | 27 | 65 | 2 | 2 |
| 20 | TanH | Delta | 50000 | 95 | 88 | 5 | 13 | 88 | 63 | 1 | 8 |
| 21 | Sigmoid | Delta | 75000 | 72 | 94 | 28 | 6 | 24 | 65 | 3 | 2 |
| 22 | Sigmoid | Ext. BPB | 50000 | 72 | 94 | 28 | 6 | 26 | 65 | 3 | 2 |
| 23 | Sigmoid | NCuDelta | 250000 | 73 | 94 | 27 | 6 | 27 | 65 | 3 | 2 |
| 24 | Linear | Delta | 500000 | 74 | 94 | 26 | 6 | 26 | 65 | 3 | 2 |
| 25 | Sigmoid | Delta | 40000 | 95 | 75 | 5 | 25 | 89 | 39 | 1 | 11 |
| 26 | Sigmoid | Delta | 100000 | 76 | 94 | 24 | 6 | 28 | 65 | 2 | 2 |
| 27 | Linear | NCuDelta | 50000 | 83 | 95 | 17 | 5 | 37 | 66 | 2 | 2 |
| 28 | Sigmoid | Delta. | 50000 | 83 | 95 | 17 | 5 | 44 | 67 | 2 | 2 |
| 29 | Sigmoid | Delta | 600000 | 83 | 95 | 17 | 5 | 42 | 67 | 2 | 2 |
| 30 | Sigmoid | Delta | 50000 | 84 | 95 | 16 | 5 | 48 | 67 | 1 | 2 |
| 31 | TanH | NCuDelta | 250000 | 96 | 74 | 4 | 26 | 91 | 36 | 0 | 17 |
| 32 | TanH | NCuDelta | 500000 | 96 | 78 | 4 | 22 | 91 | 49 | 0 | 14 |
| 33 | TanH | NCuDelta | 350000 | 97 | 79 | 3 | 21 | 92 | 51 | 0 | 14 |
| 34 | Linear | Delta | 50000 | 95 | 72 | 5 | 28 | 0 | 0 | 0 | 0 |
| 35 | Sigmoid | Ext.BPB | 50000 | 95 | 72 | 5 | 28 | 0 | 0 | 0 | 0 |
| 36 | Sigmoid | Delta | 150000 | 95 | 74 | 5 | 26 | 2 | 3 | 0 | 0 |
| 37 | Sigmoid | Delta | 70000 | 95 | 74 | 5 | 26 | 3 | 6 | 0 | 0 |
| 38 | Sigmoid | Delta | 50000 | 95 | 78 | 5 | 25 | 4 | 18 | 0 | 0 |
| 39 | Sigmoid | NCuDelta | 50000 | 95 | 78 | 5 | 22 | 4 | 29 | 0 | 0 |
| 40 | TanH | Ext.BPB | 50000 | 96 | 78 | 4 | 22 | 5 | 38 | 0 | 0 |
| 41 | Linear | Delta | 50000 | 96 | 81 | 4 | 19 | 5 | 46 | 0 | 0 |
| 42 | Sigmoid | Delta | 500000 | 97 | 86 | 3 | 14 | 5 | 61 | 0 | 0 |
| 43 | TanH | Delta | 50000 | 97 | 88 | 3 | 13 | 5 | 68 | 0 | 0 |
| 44 | TanH | Delta | 100000 | 97 | 88 | 3 | 13 | 6 | 72 | 0 | 0 |
| 45 | Sigmoid | Delta | 150000 | 97 | 89 | 3 | 11 | 7 | 74 | 0 | 0 |
| 46 | Linear | Delta | 50000 | 97 | 89 | 3 | 11 | 7 | 76 | 0 | 0 |
| 47 | Sigmoid | Delta | 550000 | 95 | 75 | 2 | 25 | 86 | 88 | 1 | 11 |
| 48 | Sigmoid | Delta | 600000 | 95 | 76 | 5 | 24 | 87 | 44 | 1 | 10 |
| 49 | Linear | Delta | 700000 | 95 | 82 | 5 | 18 | 87 | 60 | 1 | 4 |
| 50 | Sigmoid | Delta | 800000 | 95 | 83 | 5 | 17 | 87 | 64 | 1 | 4 |
| 51 | Sigmoid | Delta | 350000 | 96 | 13 | 4 | 87 | 6 | 7 | 2 | 2 |
| 52 | TanH | Delta | 30000 | 96 | 15 | 4 | 85 | 9 | 10 | 2 | 2 |
| 53 | Sigmoid | NCuDelta | 50000 | 97 | 20 | 3 | 80 | 15 | 13 | 1 | 2 |
| 54 | Linear | Delta | 750000 | 97 | 40 | 3 | 60 | 33 | 34 | 0 | 2 |
| 55 | Sigmoid | Ext.BPB | 100000 | 98 | 47 | 0 | 53 | 38 | 41 | 0 | 2 |
| 56 | Sigmoid | Delta | 50000 | 98 | 47 | 2 | 53 | 38 | 41 | 0 | 2 |
| 57 | Linear | Delta | 50000 | 96 | 31 | 4 | 69 | 20 | 24 | 1 | 2 |
| 58 | Sigmoid | TanH | 1000000 | 96 | 35 | 4 | 65 | 20 | 28 | 1 | 2 |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 59 | Sigmoid | Delta | 850000 | 97 | 35 | 3 | 65 | 20 | 29 | 1 | 2 |
| 60 | TanH | Ext.BPB | 50000 | 94 | 75 | 6 | 25 | 86 | 38 | 1 | 11 |
| 61 | Linear | Delta | 50000 | 98 | 37 | 2 | 63 | 23 | 31 | 1 | 7 |
| 62 | Sigmoid | Delta | 700000 | 98 | 51 | 2 | 49 | 29 | 46 | 1 | 2 |
| 63 | TanH | CumDelta | 100000 | 96 | 96 | 4 | 4 | 89 | 85 | 1 | 3 |
| 64 | TanH | NCuDelta | 1000000 | 97 | 96 | 3 | 4 | 91 | 85 | 1 | 3 |

**Table 7.4 Results of runs for Model B**

Key:

**HR** Healthy Right

**HW** Healthy Wrong

**BR** Bankrupt Right

**BW** Bankrupt Wrong

### 7.3.3 Model A and Model B Compared

The experimental evidence presented from this programme of work revealed some important findings when comparing the models.

For the fully connected network **(Model A),** the common approach of submitting all possible data to a neural network without any structured data organisation (i.e. domain independent) was followed. **Model A** results did not show a clear-cut deviation from the average and it has produced some very poor results. **Model A** has returned over 90% in both cases as 'don't knows'. **Model B** produced some very interesting results. This model was trained using a *priori* knowledge to organise data in the network in the same manner as financial analysts use to evaluate corporate performance. According to Simard et. al., (1998), complex neural network architectures that combine humans' a prior knowledge with information automatically extracted from a set of labelled examples (the training set) can produce models with satisfactory performance. According to Simard et. al. such networks often converge to the optimal solution.

## 7.4 Summary and Conclusions

Feed-forward neural networks as universal function approximators can estimate the *a posteriori* probabilities for a given classification problem. Their flexible mapping can provide approximations of posterior probabilities with a high accuracy level if they are modelled properly. Neural networks' mapping function (or ability) becomes particularly important for the corporate bankruptcy phenomenon where multiple estimates are combined. **Model B** achieved better prediction because of a combination of possible factors and these are mentioned below, although some can be adduced from Chapter 5.

- The high-level topology captures the temporal nature of the data as shown in Figure 6.3 (see chapter 6).
- The low-level topology uses domain knowledge to select, and organise the data in the inter-connected sub-networks.
- A total number of 84 runs (20 runs for **Model A**, and 64 runs for **Model B**) was carried out with different levels of parameter values and neural network iterations before convergence was achieved. The process involved many trials.
- The preferred architecture (with 415,012 data records) has to be fixed before learning. It was decided before learning that the preferred topology must be forced to learn with its complex non-linear boundaries in the input space. The usual procedure of starting with a small network and gradually increasing its size until performance begins to level off, with each network variant trained independently was not used. This approach will be difficult for the study due to the sheer volume of data used for training. In contrast, the *'destructive algorithm'* as suggested by Le Cun (1989) was not considered either. The study used a fixed network size with pre-selected input variables from the onset. The network was forced to learn on this criterion.
- The use of two fully connected hidden layers was adopted for experimental purpose, however, the use of eighteen hidden units was derived as a result of the trial and error process.

- It has been shown that increasing the number of training iterations and adjusting parameter values at different levels in the Global Learning Schedule can improve the generalisation performance of feed-forward networks. The modification amounts to selecting a fixed transfer function, the hyperbolic tangent, and using the Norm-Cum Delta-Bar-Rule as the learning rule. The author also varied other network parameter values (including network biases).
- It was decided before learning that without *a priori* knowledge of the problem, the complexity required cannot be known. For example, as in our case, the decision boundary is *spherical* (i.e. one class is embedded in the other), the level of network parameterisation required to approximate the boundary was arrived at after many trials. The process had been tedious and painstaking.

The study has compared the results from **Models A and B** reported in the study. **Model A** is the fully connected neural network, which submits all possible data without the use of domain knowledge to organise data in the networks. After carrying out 20 runs, it was decided that this network would not produce optimal results. Results were becoming worse than previously obtained and for this reason, it was decided to limit the total runs to 20. In this particular case, (**Model** A) the network weights were constantly moving away from their targeted values (i.e. moving away from zero). A number of training strategies (as mentioned in Section 7.3.1.1) was carried out to see if convergence could be achieved without the need for considering the use of an alternative architecture. However, the results obtained were quite disappointing. Consequently, the author had to consider the use of an alternative architecture.

**Model B** shows the use of the inter-connected sub-networks where each sub-network is connected to its immediate neighbours. For **Model B** the author started by switching between transfer and learning functions. However, there was a noticeable marked improvement in the network's results when the transfer function was fixed at the Hyperbolic Tangent (TanH) and the learning algorithm at the Norm-Cumulative Delta-Bar-Rule. From this point, the author continue to vary other learning parameters and using various strategies as mentioned in Section 7.3.2.4 until eventually optimal solution was achieved.

All the above underscores the importance of the near exhaustive data processing which had taken eighteen months to complete. Neural networks are data driven and the particular network is as good as the data used to train it. However, in this case, the domain knowledge of the author to select and organise data in the networks was equally important. The more concisely the data features describe the samples the better the eventual network.

From the evidence produced in the literature and in this chapter, there is strong evidence that neural networks are suitable for the task of bankruptcy prediction.

# CHAPTER 8

# DISCUSSION AND CONCLUSIONS

## 8.1 Overview

The preceding chapter reviewed the data collected during the study and described how domain expert knowledge was used in organising the data in the neural networks, reporting on the results from the neural network runs. The interpretation of the results was that an inter-connected neural network does provide overall improvement to the identification of bankrupt companies in the particular conditions outlined by the research issue.

Before presenting an argument for the case that this research outcome can be generalised to other conditions, this final chapter of the thesis reviews the whole research, looking again at how the focus was established and considering the strengths and weaknesses of the research during its development and conduct. Section 8.2 restates the background issues before presenting a review of the findings of the investigative research covered in chapters 2 and 3 in section 8.3. In section 8.4, the corporate failure identification approach and its implementation in the prototype neural network model are reviewed. This is followed by section 8.5, which discusses neural network training processes and the subsequent reporting and analysis of results originally reported in chapters 6 and 7. Section 8.6 identifies the implications of the research. The research limitations and future work are discussed in section 8.7. Finally, section 8.8 provides an overall summary of study.

## 8.2 The Background Issues

Finding ways of trying to identify failing companies as early as possible is clearly a matter of considerable interest to investors, creditors and auditors, especially as a significant number of British public and private companies collapse within five years of incorporation. The rate of failure amongst listed and unlisted companies is clearly a worry to financial analysts and to those investors who wishes to have knowledge of the event before it occurs so that they can minimise their losses. Corporate failure can result in financial loses, and emotional sufferings to all parties concerned. The larger the bankrupt's interface with others, the more profound the effect.

In any bankruptcy study, it is necessary to consider the meaning of the terms 'failure' and 'prediction'. The former can embrace various types of financial distress, ranging from bankruptcy at one extreme to a decline in liquidity at the other. 'Prediction' for its part can refer to an ability to foresee an event before it occurs. The ability to foresee such an event before it occurs is very difficult due to the changing nature of corporate activities, as well as, the economic and political environment in which companies conducts their businesses. Neural Networks Models are inevitably derived using financial as well as political and economic data. Neural Network Models are generally tested on a 'hold out' sample to see how well they can forecast future corporate bankruptcies.

A general weakness of bankruptcy identification models, and one discovered by this study is that there is usually little or no economic theory underpinning them, which could explain why certain financial variables have been selected in other studies (Nasir et. al. 1998). Consequently, the models could not discriminate properly between failing and healthy companies. To date, bankruptcy identification models are rather derived on ad hoc basis. Further problems which give rise to unjustified inferences are an inadequate allowance for the fact that only about 5% of listed companies in the population sample are likely to fail in any one year; and various other 'sample selection biases' (for example, data for bankrupt companies are less available) and there is inadequate allowance for industry, economic and political factors because of the use of matched pairing technique.

In a typical efficient economy, for example the UK, investors and creditors have strong incentives to identify financially distressed companies, (so that they can minimise their losses) and in particular to be first to get the news. However, any advantage gained is likely to be short lived. Nevertheless, the search for an early warning of financially distressed companies is reflected in the pressure placed upon financial analysts by their clients to warn them well in advance of impending bankruptcies. Furthermore, such warnings, when given, are not generally issued until the companies concerned are effectively beyond redemption.

## 8.3 Literature Review

This section reviews the findings of chapters 2 and 3, which reported on the literature survey performed to underpin this research. We should recall that the focus of this research was encapsulated by the following statement:

> Whether the use of domain expert knowledge and time dependent structured neural networks, can successfully discern patterns or trends in the financial data and use them as early warning signals of bankruptcy conditions prevalent in current apparently viable companies.

However, before this final focus was achieved (chapter 6, page 123), research into broader areas was performed. Initially, in chapter 1 of the thesis, Introduction, the background to the research was presented and this led to the first discussion of how the research could be focused. Recall that it is the shortcomings of discriminant analysis (e.g. the normality assumptions) and simple models of neural networks (e.g. single-point predictions) that are fuelling the need for a better prediction approach (Husmeir and Taylor, 1997; Swinger, 1996). Attempting to provide a solution to improve upon the multivariate prediction ability of time varying neural networks has been the focus of this research.

As discussed in chapter 2, most bankruptcy predictions models are derived on an ad hoc basis with little theoretical underpinning. However, there are a number of theories which inform a general understanding of corporate failure. Beaver's school of thought views financial distress as the result of disequilibrating shocks. Altman's views on chaos and catastrophes can equally well be applied to the natural sciences, the idea being that an unexpected event disturbs the equilibrium and can have disastrous 'knock on' effects. Obvious examples are the financial and emotional sufferings that follow after a supposedly known good company suddenly goes out of business. The financial loses that emanate from such an event can be catastrophic. It is therefore desirable that investors know about this well in advance.

The most widely applied models used to identify companies at risk of bankruptcy are the so-called 'univariate' models. These involve the analyst examining a series of financial variables *seriatim* one-by-one. However, the 'traditional' basis for interpreting financial statements is full of potential flaws which are rarely identified in the literature. In particular, it is essential to identify a benchmark against which to compare a ratio; and it is important to remember the criteria for assessing the significance of individual ratios. Moreover, anyone with the required practical experience in financial analysis will be aware of the fact that various combinations of economic circumstances can give rise to similar accounting numbers. It follows that unless an analyst is careful; he or she is highly likely to draw incorrect inferences from figures reported in companies' financial statements.

Univariate studies in corporate failure do not generally examine the nature of financial accounting ratios. There are obvious commonalities and interrelationships between financial ratios. There is also an implicit assumption of linear proportionality; the statistical distributions tend not to be symmetric. Financial ratios are spherical, they embed in each other that their significance, and implications can only be fully understood by the domain expert. The relevance of particular ratios tends to vary among industries and between different types of companies operating within the same sector. Consequently, this important incidence, makes it very difficult to make meaningful cross sectional comparisons on the basis of figures alone; and also indicates potential dangers of trying to construct models based on ratios, especially when data have to be aggregated across industry sectors. However, the sheer volume of data (2,500 companies) obtained randomly from a defined population sample (270,000 companies) had completely removed the need for a separate neural network to be trained for each industrial sector. The spherical nature of financial ratios and their implications across industry sectors have been contained by the study.

In fact, the first bankruptcy identification models devised were based on univariate ratios. Beaver (1966) used a single ratio, gearing, (net worth/debt) on his sample of

19 matched pairs of companies to devise a bankruptcy classification model. However, despite the apparent success of this experiment, it was not until some 30 years later that a comprehensive study along similar lines was undertaken by Beaver (1966). Beaver also used a single ratio to predict corporate bankruptcy. To test the predictive power of ratios, he used a dichotomous classification technique, and found the cash flow/total debt to be the best predictor of failure five years preceding bankruptcy. However, using the univariate technique therefore, the best known model was that of Beaver (1966), and its prima facie discriminatory power was impressive at the time and perhaps, less meaningful today (Altman 1968, Nasir et. al., 2000).

Most failure identification models that have been developed are not univariate in nature but multivariate (Altman, 1968; Altman et. al., 1977). Multivariate discriminant analysis allows for the interactions between financial variables to be measured in a particular way. However, multivariate discriminant analysis has been sharply criticised because the validity of its results hinges on restrictive assumptions (Eisenbeis, 1977; Zavgren, 1983; Coats and Fant, (1993). It had been stated by Nasir (1996), that the following two assumptions are particularly problematic for corporate failure prediction:

1. Multiple discriminant analysis requires that the decision set used to distinguish between bankrupt and non-bankrupt companies must be linearly separable. In the case of a single ratio, for example the gearing ratio, this means that a value below or above a defined threshold point (see Altman, 1968) must always signal either failed or healthy. In this instance, where two ratios are considered together (e.g. gearing and liquidity), the threshold separating the classification regions is a line, where more than two ratios, a plane.

2. Multiple discriminant analysis does not allow for a ratio's signal to vary depending on its relationship to another ratio or set of ratios. In other words, ratios are treated as completely independent. Unfortunately, these restrictions violate common sense.

Eisenbeis (1977) argues that the particular problems mentioned above and others (e.g., bias of extreme data points, multivariate normality assumption, and equal group covariances assumption) make multiple discriminant analysis incompatible with the complex nature, boundaries, and interrelationships of financial ratios. The exploratory power of discriminant procedures for financial ratio analysis is compromised, and the results may be erroneous (Toffleson and Joy, 1978).

The common type of multivariate model that can be derived is to apply regression analysis, with the dependent variable being a dichotomous fail/non-fail classification. However, it appears that some of the basic requirements of the regression model (e.g. linearity) are violated. While other studies have suggested alternatives procedures for predicting corporate bankruptcy, including Logit (McFadden, 1976); Probit (McFadden, 1976); Recursive Pationing (Breiman, et. al., 1984); Expert Systems (Elmer and Borowski, (1988), and Logit (Goss, et. al., 1991). None of these approaches has the superior mapping capability of neural networks (Hawley et. al., 1990; Groot and Wurtz, 1991; Goonatilake and Treleaven, 1995). According to (Eisenbeis, 1977 and Ohlson, 1980) statistical approaches have produced limited results especially in the case of multimodality (Husmeir and Taylor, 1997). Statistical approaches have limited practical usefulness when measuring temporal tendencies in financial data (Scott, 1978; Pinches, 1980).

However, the survey of literature conducted by the author suggests that neural network can be useful for predicting corporate bankruptcy. The readings suggest that:

- Neural networks are able to recognise patterns in financial statements data even when they are noisy, ambiguous, distorted or variable (Hoptroff et. al., 1991).
- Neural networks continue to perform well even with missing or incomplete data (Lee et. al., 1996), a task most difficult for statistical techniques, particularly multiple discriminant analysis (Eisenbeis and Altman, 1978; Eisenbeis, 1977).
- Neural networks are capable of discovering data relationships, whereas regression model building presumes knowledge of the underlying relationships (Zavgren, 1983).

The primary reason for preferring neural networks to statistical regression techniques is that neural networks have more general function forms than do other well-developed statistical methods (White, 1989). The study of White argues further that neural networks do not depend on linear superposition and orthogonal functions, which statistical regression approaches must use. Consequently, the function approximations that arise from properly applied neural networks are usually better than those provided by regression techniques. This difference is particularly important in high dimensional spaces where many of the more "automated" regression techniques often fail to produce an appropriate approximation.

Providing a large number of input parameters to a neural network does not pose a model structure problem as in regression models (Zimmermann and Weigend, 1996). If some data items turn out to be unimportant in solving the problem, the neural network will learn to ignore this by assigning near-zero values to weight the data. For example, it is rather unthinkable to attempt to submit 405,012 data records to multiple discriminant analysis without encountering serious difficulties.

However, one of the most important and quite significant results in neural computation research is the proof that neural networks are universal approximators (Refenes et. al., 1993). Given a sufficiently large amount of free parameters the learning procedure is guaranteed to find a mapping between any set of independent and dependent variables (Taylor and Lisboa, 1997). This is quite significant as it implies that neural networks can tackle the widest possible range of problems including the corporate bankruptcy phenomenon. The only possible caution here and one that should be emphasised quite strongly is that this obvious neural learning flexibility may lend itself to finding associations where none exist. Therefore the selection of both dependent and independent variables should be approached with great care and should be treated as part of the modelling construction process. The ultimate performance of the learning algorithm estimator will depend upon the relevance of the selected independent variables and the quality of the data used. Having too few independent variables constrains the search space and introduces bias which may produce generalisation error (Cater, 1987; Fahlman, 1988). On the other hand, having too many independent variables increases the dimensionality of the search space in which the procedure seeks the solution and will introduce generalisation error due to variance (Taylor and Lisboa, 1997). The appropriate balance therefore depends on the domain expert knowledge of the neural network developer. The other advantage which should mentioned here is that neural networks provide an enhanced capability to model noisy data that compose of numerous spherical characteristics and intricacies.

As discussed in chapter 3, previous research using neural networks to predict corporate bankruptcy has not focused specifically on time series processing. Over the past three decades, a large amount of literature has emerged concerning the development of the appropriate neural network architecture for predicting corporate bankruptcies. The current tendency in failure prediction emphasises the use of simple models derived from the financial data one year prior to failure. To date, most models used in company failure prediction summarise information contained in a company's financial statement by selecting a limited number of financial ratios to predict future bankruptcies (Nasir et. al., 2000). However, the properties of accounting numbers do not permit any models with few parameters to capture irregularities in financial data due to the stochastic nature of financial ratios. In fact, the neural network approaches produced so far have failed to take adequate account of the changing nature of business activities. This study proposes that there exist alternative architectures for handling time-varying tendencies in financial statements of companies. These alternative architectures have been described in chapter 5.

The evidence from previous studies, even allowing for the inevitable imperfections in the research methodologies applied, is conclusive. It appears that failure identification models derived so far are based on simple models with small data samples. The literature survey described in this thesis therefore provides the foundation on which to build further understanding of the subject domain. The methodology employed is considered highly appropriate for the investigation, allowing large historical financial data to be gathered from the best available sources despite the obvious difficulties in gathering data particularly for failed companies.

## 8.4 The Research Process

The methodology employed within this research is considered to be highly appropriate for the investigation, allowing sufficient data to be gathered for answering the research questions. In the past, numerous researchers have relied on statistical techniques to predict bankruptcies, in this research, domain expert knowledge was used to select, and organise data carefully before submitting them as neural network inputs. Apart from ratios drawn from a company's financial statements, other variables can be examined in the context of corporate bankruptcy. These non-financial indicators (see chapter 3) are also important explanatory variables (in corporate failure studies) particularly when combined with financial accounting ratios.

### 8.4.1 Data Sources

Data were obtained from three reliable sources. The financial data obtained from The London Stock Exchange is on a CD-ROM. The London Stock Exchange sent three further 'updated' CD-ROMs during the development phase. This was particularly helpful to the research since previously known healthy companies in the original CD-ROM had either gone out of business or had gone into receivership. This permitted input data to be updated immediately and accordingly. The CD-ROM sent by The London Stock Exchange allowed data to be downloaded straight to Excel and DataSculptor for further processing. The obvious advantage here is that data was not input manually to the Excel and DataSculptor thus reducing the possibility of input errors. The second source was the Jordans Financial Database of major British public and private companies obtained from De Montfort University Library. A logging system had to be used in gathering financial data regarding companies that had gone bankrupt, companies in liquidation, companies under administration, those 'under going concern situation' and also, current operating companies. The economic and political data was obtained from the Bank of England. The Chartered Institute of Bankers in England and Wales published the data.

The data collected was then processed using a specialist data processing software package (described in Chapter 6) to prepare the data for neural network inputs. Three levels of data processing were possible using specialist software produced by NeuralWare Inc. These levels are the primary level, the advanced level, and the expert level. The primary level simply normalises the input data without exhaustive search for correct distribution. The advanced level ensures exhaustive data normalisation. These two levels of data processing and preparation ensure that data inputs are as clean as possible. The expert level conducts thorough and exhaustive normalisation ensuring each line of data had the correct distribution in clean data. Training cannot be started until the data had been properly processed and accepted by the network. The data transformation and analysis tools that were used to complete the data processing task were the 'Data Sculptor' and 'NeuralWare Predict'. NeuralWare is the leading supplier of neural networks development tools, applications products, professional services, and specialised training (see Appendix 6).

### 8.4.2 Target Population

The target population comprised British public and private companies, some of which are either:

- Bankrupt
- Under Receivership
- Under Administration
- Under liquidation
- Under Going Concern Situation
- Current Apparently Viable Companies

At the time the research was undertaken, some of the companies in the sample as described above were going through corporate restructuring. A certain number of companies that were under receivership and liquidation did survive restructuring but some failed. Those companies marked as "under going concern situation" did survive the 12 months testing period and only one company did fail. The CD-ROM updates received before the end of the research study revealed the following situations:

- 2 companies under 'administration' failed completely;
- 3 healthy companies went into receivership;
- 1 distressed company went into voluntary administration;
- 1 distressed company went into compulsory (court order) administration;
- 1 healthy company was voluntarily liquidated by the its directors;
- 2 healthy companies went into compulsory (court order) liquidation;

Small companies and newly formed companies were excluded from the sample because small companies are usually run by families and sole proprietors and as such would have high propensity to failure. An owner managed company director may come to work today and decides to retire the next day. In fact, the sudden death of the proprietor may bring about the collapse of a particular company.

New companies with financial records less than three years were excluded because they are especially prone to bankruptcy. Although not having enough records does not necessarily make small companies prone to bankruptcy, but it does make them difficult to use in this research study.

Finally, the choice of the target population also prevented company characteristics and differences associated with academic discipline, domain knowledge and previous experience in banking influencing the research outcome.

### 8.4.3 Possible Definition of a Bankrupt Company

Before selection of the final data set, bankrupt companies were defined as follows:

- Those companies, which have started compulsory or voluntary liquidation;
- Those companies, which quit or have closed business.
- Those companies, which reported the withdrawal of listing or whose listing was terminated by The London Stock Exchange.

Once the above definition was clearly established, it was possible to select 2,500 companies randomly from the population sample of 270,000 companies.

### 8.4.4 Sample Selection

The sample was selected in the following way:

- Define the period of study.
- Define a bankrupt company.
- Define a non-bankrupt company.
- Define 'mates' – pair up similar companies.
- Final selection 2500 companies from potential sample size of 270,000 companies.

### 8.4.5 Variable Selection

The financial input variables used in this study are re-stated below. Recall that the time series measurement is for a period of three years.

- Data over three years: 1994, 1995, 1996.
- Input variables:

  balance sheet (10 variables)

  profit and loss statements (8 variables)

  cash-flow statements (10 variables)

  financial summary statements (6 variables)

  key financial ratios (20 variables)

  political factors data (1 variable)

  economic factors data (3 variables)
- 58 x 3 x 2500+ (4 x 3) = 435,012 data inputs to neural network.

### 8.4.6 Economic and Political Factors

Apart from financial ratios drawn from companies' financial statements, other variables can be examined in the context of corporate bankruptcies studies. The political as well economic data combined with financial ratios used in the study are repeated below for completeness:

- Bank of England Annual Inflation Rate
- London Inter-Banks Borrowing Rates
- Bank of England state of British Economy forecast
- Bank of England Borrowing Rates

A predictive variable is one which alone can explain a significant part of the variability in the dependent variable. The above listed information (independent) variables have no predictive power as such on their own but, when combined with others such as financial variables mentioned earlier, can lead to better prediction.

### 8.4.7 Neural Network Models

As mentioned in the previous chapter, two neural network topologies were considered in the study. Recall **Model A** is the fully connected neural network with 18 hidden nodes, and **Model B** is the incorporating in time neural network also with 18 hidden nodes. These architectures (see Figure 8.1 and 8.2) are repeated below for completeness.

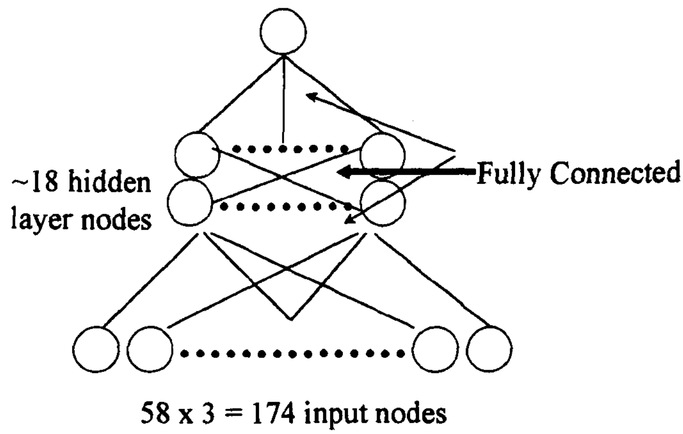



**Figure 8.1 The Fully Connected Neural Network**

**Model A** is the fully connected network with one input layer (174 units), two fully connected hidden layers and one output layer. There are links between all the nodes in adjacent layers as depicted in Figure 8.1 above. There is a separate link from the input layer to the hidden nodes and from hidden nodes to the output node. Each node has a connection strength or weight, which is stored in and maintained by the node on the receiving end of the link. The output node represents the outcomes from the network.

**Model B** is the inter-connected neural sub-network each connected to its immediate neighbour as repeated in Figure 8.2 below.

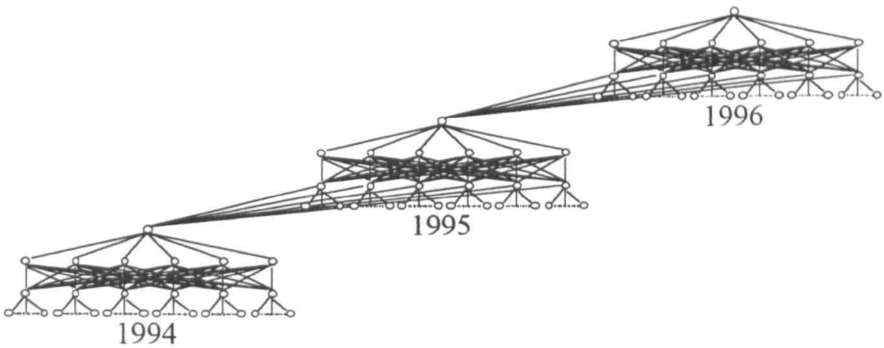



**Figure 8.2 Inter-Connected Neural Sub-Networks**

The above model is made of a series of inter-connected networks each connected to its immediate neighbours. Thus the hidden layer in 1995 receives additional input from the previous 1994, the hidden layer of 1996 receives additional input from the previous 1995, and this provides an encoding of a three-year period. There is a feedforward connection between the input units to the first hidden layer and full connection between the two hidden layers. This high-level topology captures temporal nature of the data. The low-level (i.e. connection between input units to the first hidden layer) topology of sub-networks uses domain knowledge. The input to this network includes the entire three-year historical series of the indicators used. The sub-networks are compartmentalised into three separate years. This is similar to the work of a financial analyst when examining the historical time series of financial statements over a pre-defined period of time, and thus reflects the application of domain knowledge to this problem.

The software used for this work is NeuralWare Professional Development Plus/2 System (NeuralWorks™ 2/Plus v5.30, 1996). The overall environment forms an efficient and easily expandable tool for methodological development. The tool allows selection from any of the major network types to create any of the 28 major paradigms and dozens of variations. Trained neural work can be instantly transformed an ANSI standard C source code. This allows a particular network to be constructed and the C source code instantly generated if required.

### 8.4.8 Data Processing Problems

Chapter 2 has described in detail how the missing values have been dealt with in this thesis. All the sub-categories of multivariate non-normality are repeated below.

- Multivariate non-normality.
  - Missing data.
  - Descriptive data.
  - Hidden data.
  - Creative accounting practices (e.g. window dressing).

The treatment of the missing values was checked by an independent expert and a separate study was conducted by the author as presented by Nasir et. al., (1998). That paper proposed ways of handling missing values in financial data.

## 8.5 Training the Neural Networks

As mentioned previously (see chapter 5), domain expert knowledge was used to organise data in the networks. After a very successful data processing task, it was decided to commence network training. Back propagation neural network algorithm was used for training the networks in the study. The backpropagation neural network algorithm is the most widely used for pattern classification problems (Medsker et. al., 1996). According to Medsker and Liebowitz (1994), backpropagation neural network algorithm requires large patterns to converge to small errors. However, this particular problem was not problematical for the study because of the sheer volumes of data used in training the networks. Nevertheless, it took long time to converge.

Learning problems in backpropagation neural network algorithm occur when they are required to map a well-defined set of input units into a well-defined set of output units. They can generally be solved by use of hidden units and several levels of network parameterisation.

The network creates its own best possible set of outputs for the given inputs. No knowledge is supplied about what classifications (outputs) are correct, and those that the network derives may or may not be meaningful to the person training the network. The problem in this research is necessarily a classification problem where previous knowledge of the author is supplied to the network.

As mentioned in section 8.4.7 above, two types of network were considered in the study. **Model A** is the fully connected neural network and **Model B** is the inter-connected neural network architecture. **Model B** produces the best outcome for this research and its actual outcome is re-produced here for completeness.

| | |
|---|---|
| RUN NO: | 64 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | TanH |
| LEARNING RULE | Norm-Cum-Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 1000000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 200000 | 200000 | 200000 | 200000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 3 | % bankrupt don't know | 3 |
| % Healthy right | 96 | % healthy wrong | 3 | % healthy don't know | 1 |

Classification Criteria 0.10 and 0.90

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 90 | % bankrupt wrong | 3 | % bankrupt don't know | 7 |
| % Healthy right | 95 | % healthy wrong | 1 | % healthy don't know | 3 |

Classification Criteria 0.05 and 0.95

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 91 | % healthy wrong | 1 | % healthy don't know | 9 |

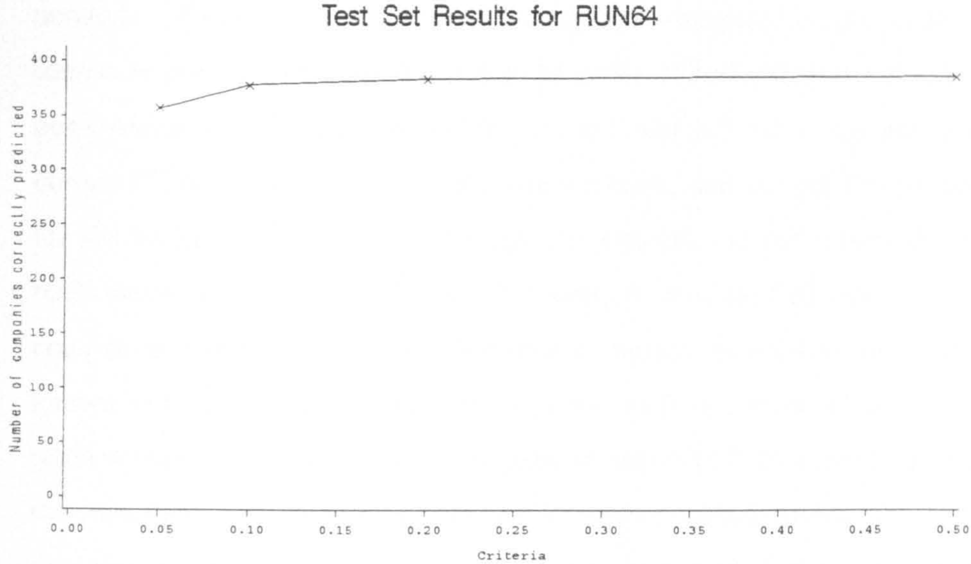



**Figure 8.3 Performance showing Bankruptcy Scale**

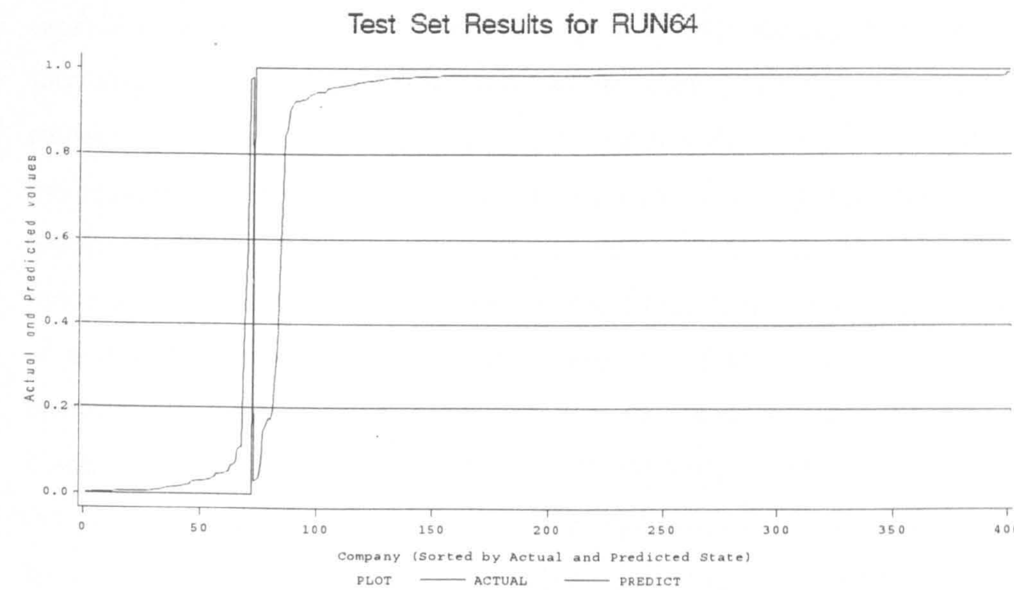



**Figure 8.4 Performance showing actual and predicted values**

The input units in the above network represented data values for various financial, economic and political measurements as detailed in Table 4.1 (see chapter 4). When checking the output neuron values for the above network, the prediction results were very promising. Two testing thresholds will used to test the predictive capability of the network. These testing thresholds identify how stringent the allowable variation in output neurons can be when predicting the status of both categories (i.e. bankrupt and non-bankrupt) in the test set. Using the 0.5 and 0.5 basis, the network achieved correct (97%) classifications for the non-bankrupt, and correct (96%) classifications for the bankrupt companies. Although the network did not return any company in both categories as 'don't know', however, it misclassified 3% of non-bankrupt companies as bankrupt and 4% of bankrupt companies as non-bankrupt. The former is known as type 1 error and the latter is known as type 2 error. Using criteria that are more stringent; i.e. 0.05 and 0.95, the network achieved 91% correct classifications for the non-bankrupt companies and 85% correct classifications for the bankrupt companies. The input units in the above network represented data values for various financial, economic and political measurements as detailed in Table 4.1 (see Chapter 4). When checking the output neuron values for the above network, the prediction results were very promising. Two testing thresholds will used to test the predictive capability of the network. These testing thresholds identify how stringent the allowable variation in output neurons can be when predicting the status of both categories (i.e. bankrupt and non-bankrupt) in the test set. Using the 0.5 and 0.5 basis, the network achieved correct (97%) classifications for the non-bankrupt, and correct (96%) classifications for the bankrupt companies. Although the network did not return any company in both categories as 'don't know', however, it misclassified 3% of non-bankrupt companies as bankrupt and 4% of bankrupt companies as non-bankrupt. The former is known as type 1 error and the latter is known as type 2 error. Using criteria that are more stringent; i.e. 0.05 and 0.95, the network achieved correct (91%) classifications for the non-bankrupt companies and 81% correct classifications for the bankrupt companies. For this criterion, the network did return 9% of non-bankrupt and 13% of bankrupt cases as 'don't knows'. It misclassified 1% of non-bankrupt companies as bankrupt and 3% of bankrupt companies as non-bankrupt. classifications for the bankrupt companies. For this criterion, the network did return 9% of non-bankrupt and 13% of bankrupt cases as 'don't knows'. It misclassified 1% of non-bankrupt companies as bankrupt and 3% of bankrupt companies as non-bankrupt.

The result produced by the study underscores the importance of the near exhaustive data processing and preparation which had taken eighteen months to complete. Neural networks are data driven and the particular network is as good as the data used to train it. From the evidence produced in the literature, there is strong evidence that neural networks are suitable for the task of bankruptcy prediction (Odom and Sharda, 1990).

## 8.6 Implications of the Research

The current tendency in corporate failure prediction emphasises the use of statistical techniques and simple models of neural networks to identify impending bankruptcies. This research provides a comprehensive and structured approach necessary to develop neural network models to identify perilous conditions of bankruptcy in the financial statements of current operating companies. The research techniques described earlier have been used to develop generalisable models of inter-connected neural networks.

This research represents the first attempt to use:

- A large data sample spanning over three years from 2500 companies.
- Domain expert knowledge to choose input (financial) variables.
- Domain expert knowledge to organise the data in the neural networks.
- Domain expert knowledge to select the most appropriate neural network architecture from six neural network topologies as described in chapter 5.
- An Inter-connected neural network based on three years of financial data so that the conditional probability density for the time series is captured.
- A neural network which tend to generalise very well from large sample.

The research study could be applied to similar domains where the decision making is very dynamic and based on very specific situations. For example, it could be applied to make decisions regarding an application for a loan, corporate ratings, and lending for a particular purpose. Other financial analysis domains could benefit from this research method to investigate the decision-making processes for example, mortgage lending, identifying delinquent customers, and credit scoring.

In retrospect, a financial analyst would benefit immensely from this research if the methodology described in this research were followed.

## 8.7 Possible Research Limitations and Further work

It is arguable that this research suffers from a few methodological limitations. These limitations are listed succinctly below.

1. The research did not consider trying other neural network paradigms. For example, the Self-Organising Feature Map (SOM) Networks which attempts to learn a topological map from an N-dimensional input space to a two-dimensional feature were not considered because the problem at hand is a classification problem rather than a clustering problem.

2. Although six neural network architectures were considered in chapter 5, the fully connected and the inter-connected neural networks were used in the study. Although the reasons for rejecting other topologies has been discussed in chapter 5, however, it will take a considerable amount of time to train all the architectures suggested in chapter 5. The preferred architecture (**Model B**) provides a parsimonious representation of the structure of domain knowledge.

3. Although sample data for 2,500 companies were used, it is possible to increase this data sample. However, the data set used by this study is significantly larger than samples used by previous research (see chapter 3).

4. A total number of 84 runs (20 for the fully connected and 64 for the inter-connected) were carried out. However, it is possible to increase the number of runs. Increasing the number of runs will be less optimal since after convergence has been reached, any increase will decrease the generalisation capability.

5. Although it is possible to increase the number of financial variables used, it was considered that the 58 variables used for each year (1994, 1995, 1996) were sufficient. It is also possible for other financial variables to be considered.

A number of issues have arisen from the research that could warrant further investigation.

- The input variables used in this research are only 58 variables for each year thus making 174 input units for the three-year period. A theorist could argue that the input space should be enlarged to accommodate more input variables. However, from a practical point of view, the input variables selected were derived from previous experience in banking as a corporate lending banker of several years' experience and training. Bearing in mind that 54 financial variables were used in the study, it is difficult to see the need for other variable (s) to be considered.

- The data sample is large enough and indeed, it contains all the major British public and private companies. However, a theorist could argue that the final selection of 2,500 companies from a possible 270,000 companies should be increased. From a practical point of view, the final selection contains all the possible characteristics of failure as seen in the collapse of most companies. However, it must be remembered that this final selection represents 435,012 data records submitted to the network.

- It could be argued that all the architectures mentioned in the study should have been used in the study before arriving at the conclusion that **Model B** offers the best approach.

## 8.8 Summary

*A priori* reasoning suggests that it ought to be very complex and quite difficult to devise corporate failure identification models for listed and unlisted companies which will consistently be able to detect future bankruptcies. This is because corporate activities change over time and failure prediction is not susceptible to simple equations that could easily be solved by rule of thumb. Yet despite these difficulties, the fact is that it is often possible to predict impending bankruptcies if the model has been developed properly. This research has shown that neural networks can successfully discern patterns or trends in financial data of companies and use them as early warning indicators of bankruptcy conditions prevalent in current apparently viable companies.

A close examination of previous empirical work suggests that since 1932 academics have spent too much time in developing statistical procedures to apply to numerous different types of independent explanatory variables. However, very little results have been produced. Although it has to be said that in early years of corporate failure studies, statistical methods had been the only possible methods. In fact neural network only came to the scene early 1980s (Grossberg, 1988). More recently, a large number of simple models of neural networks have been developed to predict corporate bankruptcy. The former approach suffers from normality assumptions, and the latter is inappropriate when measuring temporal tendencies in financial data. The properties of accounting numbers do not permit any models with few parameters to capture the irregularities in financial data due to their stochastic nature.

This research has identified a constructive neural network methodology that can be combined with domain expert knowledge. As described in chapter 5, *a priori* knowledge in the domain was combined with three sub-networks (inter-connected) with a large data sample (2,500 companies) to model the identification of probable bankruptcies. The results described in chapter 6 show that artificial neural networks can be particularly useful in improving multivariate prediction capability. Since corporate failure does not follow a random walk, it is possible to devise failure identification models that will signal probable bankruptcies. A neural network has been successfully used to recognise patterns in the financial data submitted to the network.

The main thrust of the research findings provided evidence to address the research issue. This issue can be re-stated as follows:

> *Whether combining domain expert knowledge with neural networks can help to predict corporate bankruptcies.*

The study was then focused on providing evidence to address the above issue. As noted in chapters 2 and 3, it was necessary to carry out investigation on previous work in this area to avoid repeating the same mistakes again. In chapter 4, domain expert knowledge was used to obtain the appropriate financial data. Chapter 5 discussed neural network design considerations and selecting the preferred topology. Chapter 7 presents the study results for Models A and B to support the above research issue.

One generality of the research, not particularly highlighted before, is that the approach is not confined to use in identifying bankrupt companies but also to other financial areas where human judgements are constantly required before making a decision. Possible uses could include, for example, the use of score cards presently being used by financial analysts to decide whether to grant or refuse a loan application from a corporate customer. The research reported in this thesis shows one way forward for the use of neural networks in identifying bankrupt companies, and that, though there are problems and pitfalls to be overcome, especially with misclassification errors, there are gains to be achieved from a corporate failure identification model since this would help equity investors to minimise their losses. There are bright possibilities to be sought in the future by all those concerned with identifying bad companies.

Finally, in the research study we have preferred the use of inter-connected neural sub-network to predict corporate bankruptcy. The two models produced in the study differ in their structures and layers connectivity. Our methodology for neural model selection, variable selection and different levels of network parameterisation produced a neural network model, which outperforms discriminant analysis, and the use of simple models of neural networks described in chapter 4. In a nutshell, (a) the results strongly indicate the presence of non-linear relationships between input data and corporate bankruptcy, and (b) demonstrate the ability of our proposed methodology to provide a neural network approach for dealing with the problems of pattern recognition in the financial data of companies.

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## Appendix A – Author's Publications and External Reviewers' Comments

This section contains samples of accepted papers and reviewers' comments from the author's publications related to the PhD work.

1. Nasir, M.L. (1998): "Combining Expert Knowledge with Artificial Neural Networks for the Predictions of Corporate Bankruptcy". *Proceedings of the first Recent Advances in Soft Computing, De Montfort University*, Leicester.

2. Nasir, M.L., John, R.I., and Bennett, S.C. (1998): "Financial Data Sampling and Selection for use in Artificial Neural Networks". *Proceedings of the IV International Meeting on Artificial Intelligence and Emerging Technologies in Accounting*, Finance and Tax". University of Huelva, Spain.

3. Nasir, M.L., John, R.I., and Bennett, S.C. (1999): "Predicting Corporate Bankruptcies using Inter-connected Artificial Neural Networks", *Proceedings of the European Congress on Intelligent Techniques and Soft Computing*, Aachen, Germany.

4. Nasir, M.L., John, R.I., Bennett, S.C., Russell, D.M., (2000): "Predicting Corporate Bankruptcy using Artificial Neural Networks" ***Journal** of Applied Accounting Research*, Spring.

5. Nasir, M.L., John, R.I., Bennett, S.C., Russell, D.M. (2000): "Handling Non-Convergence in Time Varying Neural Networks", *Proceedings of Joint International Conference on Neural Networks*, May 15-17, 2000, Pittsburgh, USA.

6. Nasir, M.L., John, R.I., Bennett, S.C., Russell, D.M. (2000): Extended Version: "Predicting Corporate Bankruptcies Using Modular Neural Networks", In *IEEE TRANSACTIONS ON NEURAL NETWORKS on Neural Networks in Financial Engineering*, Special Issue: Tentative Publication Date: May 2001.

7. Nasir, M.L., John, R.I., Bennett, S.C., Russell, D.M. (2000): "Selecting the Appropriate Neural Network Topologies for the Predicting Corporate Bankruptcies" In *Proceedings of the Third International Conference on Artificial Intelligence and Soft Computing (The American Association for Artificial Intelligence)*, July 24-26, 2000, Banff, Alberta, Canada.

8. Nasir, M.L. (1996): "An Evaluation of the Application of the Corporate Bankruptcy Prediction of Artificial Neural Networks". Research Monograph 1, De Montfort University, Leicester.

9. Nasir, M.L., John, R.I., Bennett, S.C. "Financial Data Sampling and Selection for use in Artificial Neural Networks", De Montfort University Working Paper No.2, 1999.

10. Nasir, M.L. (1996): "Predicting Corporate Bankruptcies using Artificial Neural Networks". A transfer to PhD Document: De Montfort University, Leicester.

11. Nasir, M.L. (1997): "Corporate Bankruptcy Prediction using Artificial Neural Networks". Proceedings of the first Postgraduate Conference, De Montfort University, Leicester.

12. Nasir, M.L. (1998): "Corporate Bankruptcy Prediction using Artificial Neural Networks". Proceedings of the second Postgraduate Conference, De Montfort University, Leicester.

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*Special Issue*
*IEEE TRANSACTIONS ON NEURAL NETWORKS*

September 1, 2000

Dr. Mohammed Lateef Nasir
Phd Research student
Faculty of Computer Science and
Engineering
De Montfort University The Gateway
Leicester LE1 9BH United Kingdom

RE: Manuscript Number 124
Using Evolutionary RBF Networks for Credit Assessment

Dear Dr. Nasir

Thank you for agreeing to review the manuscript listed above which has been submitted for possible publication in the special issue of the *IEEE Transactions on Neural Networks* on "Neural Networks in Financial Engineering". It would be greatly appreciated if you could return your completed review by November 15, 2000. A review form is enclosed for your convenience. To expedite the process however, you can email me your review if you wish. My email address is amir@work.caltech.edu.

Thank you very much for your time and assistance.

Sincerely

Amir Atiya
California Institute of Technology
Mail Stop 136-93
Pasadena, CA 91125 USA

Enclosures

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**Manuscript No.:** **124**

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**Reviewer's(s) Name:** Dr.    Mohammed Lateef Nasir

**Review Signature:** ______________________    **Date:** ______________

1. CONTENT: (Please detail your responses, as required, on page 2.)
   Answer Poor, Average, Good or Excellent.
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   Answer Low, Average, High.
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   Answer No, Not Clear, Yes.
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   - **d.** Is the order of presentation satisfactory?
   - **e.** Is the English satisfactory?
3. RECOMMENDATION:
   - ___ **ACCEPT** in its present form
   - ___ **REVISE AND ACCEPT** (Editor-in-Chief will check corrections)
   - ___ **REVISE AND RESUBMIT**
   - ___ **REJECT** and do not encourage re-submission

   (major revision and re-review by the Reviewers and/or the AE)
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   (use additional paper if necessary).

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**Manuscript No.:** 124 **Referee No.:** 013

**TITLE:** **Using Evolutionary RBF Networks for Credit Assessment**

5. COMMENTS AND SUGGESTIONS FOR AUTHORS(S):

Please typewrite or print comments and suggestions for the author(s). the objective is to guide possible revisions to improve the quality of the manuscript or to explain reasons for rejection. Please do not identify yourself or your organization; a copy of this page will be sent to the author(s).

# EUFIT '99

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Mr. Mohammed Lateef Nasir
De Montfort University
Centre for Computational Intelligence
The Gateway

Leicester LE1 9BH
United Kingdom

Aachen, 06.05.1999

**Acceptance and schedule of your contribution**

Dear Mr. Nasir,

We are pleased to confirm that your paper entitled

**Predicting Corporate Bankruptcy Using Inter-Connected Artificial Neural Networks**

has been accepted for presentation at **EUFIT '99** from September 13-16, 1999 in Aachen, Germany. Your paper with the co-author(s) R.I. John, S. C. Bennett has the reference number **12705.** It is scheduled in Session **BC 7: Financial Engineering** which will take place on 15.09.99 at 13:30:00.

A draft of the programme is attached. Please check the announcement of your paper carefully and contact us if you want to have some modifications. The final version will be available at http://www.mitgmbh.de/eufit/ at the end of May.

Please find also enclosed the paper review form, the registration form for the conference and the 'Information for Speakers'. We kindly ask you to send the enclosed hotel registration form directly to the aachen tourist information. They will arrange your accomodation.

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Best regards,

Karl Lieven
Chairman Organisation Committee

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**Paper Title: Predicting Corporate Bankruptcy Using Inter-Connected Artificial Neural Networks**

**Author(s):** Mohammed Lateef Nasir
R.I. John, S. C. Bennett

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| Relevance to the Conference | ☐ Excellent | ☒ Very Good | ☐ Good | ☐ Fair | ☐ Poor |
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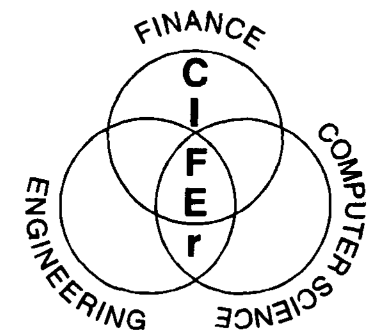


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February 16, 2000

M.L. Nasir
Centre for Computational Intelligence
De Montfort University
The Gateway, Leicester LE1 9BH
United Kingdom

Dear M.L. Nasir:

Thank you for the excellent job on the paper submitted for consideration in the CIFEr 2000 Conference, "Predicting Corporate Bankruptcy Using Modular Neural Networks". **Your paper has been accepted and we ask that you present the paper personally at the CIFEr 2000 conference being held at the Crowne Plaza Hotel, 1605 Broadway, New York City, March 26-28, 2000.** Your presentation is scheduled for, Tuesday, March 28, 2000, 11:00am-12:30pm during the track called "Risk Management Applications".

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March 1, 2000

M.L. Nasir
DE MONTFORT UNIVERSITY
LEICESTER,
UK LE1 9BH

Regarding: 309-011
Handling Non-convergence in Time Varying Neural Networks

All registration material are available at:
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Dear Dr.. Nasir,

Congratulations, your paper has been accepted for presentation as a regular paper at the IASTED International Conference on Neural Networks (NN 2000) which will be held May 15-17, 2000, in Pittsburgh, Pennsylvania, USA. We cordially invite you to attend the conference and present your paper. To confirm acceptance or rejection of your paper, please refer to the list of accepted papers posted on our website.

All registration materials and tour options will be posted on our web site by March 3, 2000. Please register and book your flight as soon as possible. You need to submit the following by April 5, 2000, for your registration:

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I apologize for the delay in notification. Once again, congratulations on your acceptance to NN 2000. We are very excited to be able to include your research and ideas in our conference, and we look forward to seeing you in Pittsburgh this coming May!

Sincerely,

Deborah Sung and Jakub Brogowski
Conference Managers
IASTED Canadian Secretariat
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Let us know your preferred method of audio and visual presentation. We will have overhead and LCD projection, lavalier, handheld and podium microphones.

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Dear colleague,

We are pleased to notify you that the paper that you submitted for the IV International Meeting on Artificial Intelligence and Emerging Technologies in Accounting, Finance and Tax has been accepted by the scientific committee.

In order to be published in the proceedings, the final version of your paper needs to follow the editor's instructions (see our web site listed below). Please submit the final version to my e-mail address no later than August 30, 1998.

You can obtain the registration form by connecting to our web site.

Sincerely

--
Enrique Bonson
Profesor Titular de Universidad de Economia Financiera y Contabilidad
Director, Grupo de Inteligencia Artificial en Contabilidad y Administracion de Empresas (GIACA)
Facultad de Ciencias Empresariales. Universidad de Huelva.
Plaza de la Merced, num. 2. Phone: 34-59-284625.
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June 5, 2000

Mr. M.L. Nasir
Faculty of Computer Science and Engineering
De Montfort University
The Gateway, Leicester LE1 9BH
United Kingdom

Dear Mr. Nasir,

Re: Paper Number: 316-039
Selecting the Neural Network Topology for Predicting Corporate Bankruptcy

Congratulations, your paper has been accepted for presentation at the IASTED International Conference on Artificial Intelligence and Soft Computing (ASC 2000) to be held July 24-26, 2000, in Banff, Canada. We cordially invite you to attend and present your paper at the conference. We also encourage you to register and book your flight as soon as possible, if you have not already done so.

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Registration materials will be available shortly on our web site (www.iasted.com). If for any reason you have trouble registering online, please send an email message to calgary@iasted.com and we will send you alternate registration information.

Once again, congratulations on your ASC 2000 acceptance. We are very excited to be able to include your research and ideas in the conference, and we look forward to seeing you in Banff this coming July.

Sincerely,

Jakub Brogowski
Conference Manager

## 1. INTRODUCTION

The collection of financial data for modelling bankruptcy prediction in Artificial Neural Networks presents two major problems. The first concerns the verifiability of the data source. Since the data is secondary i.e. financial data that have been prepared by company directors and published as annual financial statements, there is bound to be some question about the validity of the data, their groupings, and their appropriateness to the study. To confront this confounding problem, data collected should be from a substantial authority that regulates the activities and reporting requirements of the companies in the population sample. This is important in order to reduce noise in the data sets. The second problem relates to the availability of financial variables in the financial statements of the overall companies for study. Betts and Belhoul (1987) suggest a composite concept called "industry characteristics." They affirmed that a human filter should be used to gather, organise, and quantify data according to several financial ratios, based on their knowledge of the economic characteristics of the firms in the population. Two major problems can be identified with this approach. One is the diversification of operations which is common with most firms these days. There is considerable difficulty in classifying a firm into a single industry. This is partly due to the nature of the data available, and this problem is particularly difficult where a large sample is to be selected. The second problem involves the possibility that an "industry" will change over time according to how diverse operations are classified. The best available quantifiable standard against this problem is to attempt a qualitative matching of the entire population with industry characteristics, by way of explaining the groups that are derived. This does have its inherent limitations. Nonetheless, this appeared to offer the best available quantifiable standard against which to justify the selection process.

An important contribution of this paper is to focus the attention of neural network researchers on the need for a sound theoretical framework in data sampling and parameter selection for bankruptcy study. The organisation of this paper is structured as follows. In section 2, financial sample selection and data collection is addressed. In section 3, the guiding principles in selecting financial parameters are formulated. In section 4, the approaches for handling non-normality in financial data are described. Finally, a summary is included in section 5.

## 2. SAMPLE SELECTION AND DATA COLLECTION

Over the years, researchers in the field of financial engineering (Alici and Valtchanov, 1994; Altman, 1968; Betts and Belhoul, 1987), have been confronted with the task of finding a reliable sample of failed and healthy firms for which financial statements could be obtained. This is in the context of the availability of data on a large number of bankruptcies which could have been obtained from the London Stock Exchange and also from the Registrar of Companies in the UK.

### 2.1. Defined Criteria for Selection

Care should be taken when collecting financial statement data to define explicitly from the onset the criteria for selection (Lipmann, 1984). In modelling corporate bankruptcy for example, a definition of failure should be adequately defined before the selection can begin. For example, state of bankruptcy could be defined as follows:

- The firms which have applied for, have started, or are under the process of corporate elimination from records of healthy firms.
- The firms which quit or have closed business.
- The firms which have had large losses disproportionate to their assets for a particular period.
- The firms which reported the withdrawal of listing or whose listing was terminated by The London Stock Exchange.

On the other hand, nonfailed firms are firms that are still on the London Stock Exchange register of nonfailed firms including the Unlisted Securities Market (USM). The selection of successful (nonfailed) firms should be made from the listing of operating firms by the London Stock Exchange. There has been considerable discussion in bankruptcy studies about what constitutes a nonfailed firm (Argenti, 1976; Lipmann, 1984). A firm is said to be 'nonfailed' on the basis that it will continue in operational existence for the foreseeable future (David et.al., 1997). This means in particular that the balance sheet and profit and loss account assume no intention to or necessity to liquidate or curtail significantly the scale of operations (David et.al., 1997). The appropriate period to test the degree of 'nonfailure' should be twelve months from the date the financial statements were published. A period beyond this will be inappropriate because bankruptcy can occur at any time. An extraordinary event (e.g. loss of a major supplier) can collapse a firm otherwise known to be very successful. However, one can be reasonably confident that on the basis of the firm's current financial statements, the firm will not fail in the foreseeable future: usually within the next twelve months, all things being equal.

## 2.2 Obtaining a sample

A list of bankrupt firms is frequently derived using the London Stock Exchange Official Year Book (Timbrell, 1997) for publicly registered companies and Jordans (Duffy, 1997) financial database of both registered and unregistered companies, large or small. These sources represent the most substantial authority in the United Kingdom (David et.al., 1997). The London Stock Exchange is among the authorities in the UK for controlling the activities and reporting requirements of all registered companies in the UK (David et.al., 1997). The other approach to obtaining a sample is to check to see which firms have been deleted from regularly released lists of the London Stock Exchange Year Book (David et.al., 1997). Since only current successful firms will be reported in the Year Book, a separate register exists for failed firms (David et.al., 1997). Although the decision whether to include or exclude new firms depends on the period of study, it is better to exclude new firms in bankruptcy studies because new firms have the characteristics of being "small" in their first few years and because they will not have valid records sufficient enough to be relied upon. Although great attention has been directed toward the influence of asset size and the characteristics of being "small", there are certain statistical reasons for believing that asset size alters the relationship between size and failure. It can be argued that small firms will have insufficient asset size and records during their infancy. Having said that, the importance of this bias is undeniable since small firms have an especially high propensity for failure (Altman, 1993; Argenti, 1976). However, an exception to the general bias of studies toward large firms is the paper by Lipmann (1987), who studied failures among small firms. He asserted that "new firms, are likely to be excluded from most samples because they will be small and because many researchers want five or more years of data in order to test the capability of the model to forecast failure five or less years ahead."

Once a sample of failed firms is obtained, a control sample of healthy firms should be drawn up (Betts and Belhoul, 1987). This could produce some problems. If healthy firms were drawn at random, there would probably be substantial differences between the two groups in terms of size and industry. The result is that the model in attempting to discriminate between failing and healthy firms may actually be distinguishing between large and small firms, or between manufacturing or other industrials, for example (Altman; 1993, Argenti; 1976). To confront this problem, these confounding influences should be controlled by matching the failed firms with healthy firms according to their industry and size (Alici and Gifford, 1995).

## 3. CHOICE OF INDEPENDENT VARIABLES

Before proceeding to discuss the guiding principles in selecting financial parameters as input units to neural networks, we would suggest that the following considerations should govern the process of data and ratio selection:

- data availability that permits the calculation of ratios across firms in the selected sample;
- financial ratios in the selected sample that cover the period of study;
- reasonableness and general acceptability of the ratios in relation to their intended use;
- the development of a comprehensive set of ratios by types: e.g. profitability ratios, activity ratios, liquidity ratios, and indebtedness ratios, etc.

### 3.1 Theoretical background

To date, literature on corporate failure studies has failed to present a solid theoretical background in the choice of independent variables (Alici and Valtchanov, 1994; Altman et.al., 1994; Aziz et.al., 1988). Ideally, the developer should formulate from the onset the economic theory in choosing those variables that will predict bankruptcy. .This initial process is crucial if a meaningful approach is to be undertaken. It is not surprising that some researchers (Alici and Valtchanov, 1994; Altman, 1968; Argenti, 1976) have focused solely on the ratios themselves rather than providing a sound theoretical background behind their variable selection process (Alici and Valtchanov, 1994; Altman, 1994; Aziz et.al., 1988). Most of the so-called sophisticated models (Alici and Gifford, 1995; Altman, 1968; Argenti, 1976; Aziz et.al., 1988) have been based on statistical or mathematical literature and have not provided economic theory to aid in independent variable selection. It has to be said that the lack of theoretical background is not necessarily an impediment to the researcher interested in bankruptcy study. However, an important contribution is that researchers should bear in mind economic theories in parameter significance estimation and financial prediction. As will be explained later, even without a theoretical foundation, relatively accurate prediction has been developed (Alici and Valtchanov, 1994; Altman, 1994). Of course, without an economic understanding of bankruptcy, it will be difficult to ascertain whether such models are appropriate for predicting bankruptcy. If the interest is in understanding bankruptcy rather than merely predicting it, there must a capacity to apply economic interpretations to the models (Lee and Wu, 1988). According to Nasir (1996) theory would suggest a causal link between selected variables and financial distress; the proposed linkage could then be tested by an appropriately constructed model.

Unfortunately, the lack of sound theoretical background has prevented the comprehensive use of economic reasoning in selecting financial variables. The worrying aspect of bankruptcy study is that economic theory has played a limited role in failure prediction. Models produced so far (Alici and Valtchanov, 1994; Alici and Gifford, 1995; Lau, 1987) have not been able to express the significance of the institutional environment in which financial statements are produced, or used. These models have a relatively high degree of error in the results because of the lack of sound economic reasoning behind ratio selection.

However, the complexity of the issue and the historical lack of success in developing a better failure model do not necessarily imply that a useful theoretical construction is impossible. It may be that theory may be developed inductively from observation, i.e. by taking a cursory look at financial statements and their descriptive information before embarking on bankruptcy study. Further, the lack of economic theory behind ratio selection does not deny the possibility of some economic interpretation of empirically derived models (Altman, 1993; Casey and Bartczak, 1984).

## 3.2 The Search for Independent Variables

Because of the lack of theoretical support, researchers have had to search for other guides in variable selection. For example, Beaver (1977), Altman (1968), and Alici and Valtchanov (1994) have selected financial ratios as predictor variables because of their popularity and predictive success in previous studies. Although the approach has had little success in developing theory (in terms of identifying causal relationships), there has been considerable success in using the variables to distinguish between failed and nonfailed firms.

It would seem that it is not difficult to achieve whatever level of success there may be using a variety of ratios even without domain expert knowledge. According to Argenti (1976), there are several financial ratios to choose from for corporate failure study. It is the inability to select only the appropriate predictors of failure by non-expert developers that is the main concern of this study. This study will address this phenomenon.

The importance of sound economic theory in choosing financial variables cannot be over emphasised. The lack of prominence of economic theory in bankruptcy study has led to corporate failure models being developed on a single ratio. For example, Beaver (1977) focused on cash flow as a single determinant of failure. His model was based on using financial distress (cash/debt) as an indication of failure. There is a justifiable scepticism surrounding Beaver's seminal work. Because of the lack of theoretical foundation in his work, his original work achieved limited success and was quickly derided by leading commentators (Altman, 1968; Altman et.al., 1994; Aziz et.al., 1988). Argenti (1976) tried to apply Altman's model to UK based firms but failed miserably. What followed was the celebrated work of Altman (1993) which did enjoy fervent adherence throughout the world. However, Altman's work lost its credibility because it suffers from normality assumptions.

It has been observed that sophisticated models of financial distress cited in the literature generally come from the statistical (Alici and Gifford, 1995) or mathematics literature (Aziz et.al., 1988), which are of limited assistance in selecting predictor variables. It is not suggested by this study that a complex economic model is required in order to describe significance parameter estimation for financial prediction. However, it can be argued that in order to obtain maximum quality, based on the levels of certain predictors of failure, and other decision variables (descriptive information), subject to changes over time because of increasing and varying corporate activities, the selection of financial variables for corporate failure modelling should be backed by sound economic foundation. Further, the ability to employ numeric, economic and political indicators is probably the appropriate way forward for bankruptcy study. Making deductions from numeric information alone in companies' financial statements for bankruptcy study would certainly produce models of limited applicability (Alici and Valtchanov, 1994; Alici and Gifford, 1995; Beaver, 1977).

Of course, without an economic understanding of bankruptcy, it will be difficult to ascertain whether a model developed from data from one set of companies is appropriate for predicting the bankruptcy of a company operating in a different economic or temporal setting (Casey and Bartczak, 1984). This weakness is mitigated to some extent by validating the model with a holdout sample (independent test set) from a different period. However, if the interest is in understanding bankruptcy rather than merely predicting it, there must be a capacity to apply economic interpretations to the selection of predictor variables.

It is the main theme of this paper to suggest a constructive approach which will form a framework for future study. In an attempt to discover which economic variables are most related to bankruptcy, researchers should examine economic indicators identified by their own experience known from practice. Further, The London Stock Exchange Year Book (Timbrell, 1997) provides other guiding principles in financial ratio selection. Incorporating national indicators directly in a cross-sectional sample will be useful in distinguishing between failing and nonfailing firms.

If the primary concern is success in bankruptcy prediction, there is no reason to limit the study to financial ratios (Lipmann, 1984). It may be that economic and political data supplied by the Bank of England and by the Department of Trade and Industry can be useful for prediction (David et.al, 1997). It is the lack of exploitation of descriptive and economic information from corporate reports that will remain a major concern in bankruptcy studies. There has been a strong tendency to rely on glossy financial statements. Numeric information from corporate reports may show a buoyant position but it is the descriptive information that may be a pointer to financial distress. Therefore, equal prominence should be given to both when selecting predictors of failure.

### 3.3 Reducing the variable set

The lack of a theory of bankruptcy invites the researcher to consider a multitude of variables. In their studies, Altman et al (1994) and Argenti (1976) present a table that lists 250 ratios that have been useful in predicting financial distress in ten studies. Nasir (1996) suggests that using too many ratios can actually make a model less useful. He suggested further that a model is built on a "derivation sample" with known incidences of bankruptcy. The basic argument of his study is that a model that uses too many ratios may be overfitted, so that it is highly successful in classifying the sample data set, but less effective in application. It has to be said that a model that employs every possible financial indicator of failure is likely to have substantial multicollinearity. This would inevitably place greater demands on the model, since one must assume that the intercorrelations among the predictor variables in the derivation sample will also exist in the prediction sample.

A variety of ways to reduce the set of predictor variables have been suggested in the literature (Aziz et.al., 1988; Betts and Belhoul, 1987). Perhaps the most common is to use a statistical procedure that employs a stepwise approach. Stepwise procedures have been applied to both discriminant analysis and regression models by allowing a program to select variables based on the contribution of a variable toward some criterion (for example, in the case of discriminant analysis, the variable that contributes most in separating failing firms from nonfailing firms will be selected first by the stepwise procedure).

Experience from practice will suggest a better approach. An alternative way to reduce the variable set is to use factor analysis to group the variables in the total set. Only one or two ratios, determined to be representative of a factor grouping could be selected from each factor. These selected ratios could then be used in a customary way as suggested by the London Stock Exchange Year Book on reporting financial transactions in annual financial reports (Timbrell, 1997). The lack of popularity of using this basic approach in numerous studies confirms the lack of adequate domain knowledge in bankruptcy study. However, the important question of which variable to choose as representative of a factor has yet to be resolved. The reason for this is that the analysis of financial statements is not an exact science which can be conducted by employing simple analysis. The difficulty involved in variable reduction was noted in Lee and Wu (1988). They suggest that "the popular procedure of selecting the ratio with the highest absolute factor loading makes the selection sensitive to the sample." The problem with this approach is that a particular predictor which shows the highest absolute factor may not necessarily be the ratio to be selected. The ratio to be selected must be weighed against the basic characteristics of the firms in the population. A modeler with sufficient domain knowledge will have intrinsic knowledge about the basic characteristics of the firms in the population. This will help the researcher to know when to select a predictor with a low loading and even ignore those predictors with the highest loading. The analysis of parameter significance estimation, and its application to financial prediction would remain a complex area even where explicit knowledge exists.

The fact that numerous studies (Altman, 1993; Argenti, 1976; Beaver, 1977; Betts and Belhoul, 1987) have identified the same approach of reducing financial variables in bankruptcy study without selecting ratios based on the characteristics of the firms has given cause for concern. It is true to say that a set of financial variables could be viewed as measures of financial dimensions. The notion that financial variables in a bankruptcy study represent important financial dimensions that could be used for economic interpretation cannot be over-emphasised but equally, the characteristics of the underlying stochastic processes generating these financial variables is even more important. Rather than predictive power, the developer should be concerned primarily with the descriptive, or representative, power of financial ratios. Financial ratios should be examined at a macro level for broad industry classes, seeking a correspondence between the accounting numbers and basic industry attributes. This approach provides sound economic interpretations and does indicate a future direction in bankruptcy research.

# 4. NON-NORMALITY IN FINANCIAL DATA

Financial data may be viewed as random variables which (imperfectly) reveal information about a firm's financial and operating activities. Inferences based on such information from cross-sectional financial data will be dependent upon the characteristics of the underlying non-linearity generating these data and whether these can be identified. One possible reason for the absence of normality in financial data is a failure to achieve appropriate factorial control. The reason for this has to be that the analysis of financial statements is not susceptible to simple equations, which can be easily solved. Intuitively, when financial statements are processed and analysed, there are always multivariate problems (outliers, missing values, multicollinearity, hidden data, and creative accounting practices) which have to be dealt with if a proper input representation to neural networks is planned. Multivariate problems in financial data processing is a problem for any corporate financial analyst and for those planning to build neural networks for business decision making.

## 4.1 Handling Missing Values

The use of financial data in a variety of performance evaluations and decision-making contexts is an increasingly important area of accounting research and practice (Deaking, 1976; Lev and Sunder, 1979). A major problem with financial data is the existence of missing values. This issue poses serious problems when pre-processing financial data for neural networks. Four statistical approaches can be identified for dealing with missing values in financial data.

Deaking (1976) suggests that an averaging method can be applied to fill in the missing value with the average of the last value and the next valid value. The practical difficulty with this approach is that averaging may be inappropriate because financial parameters are not determined by trend within periods, but by taking into consideration various activities of the firm and pronouncements by the Accounting Standards Board (David et.al., 1997). For example, a company may pay corporation tax for 1994 at £34m and 1996 at £40m but report losses in 1995 and may not suffer any corporation tax on profits for the period. To apply averaging in this case would be misleading. Further, corporation tax payable on profits in one period often bears little or no relationship with the tax payable in another period. The normality assumption is therefore not valid in Deaking's work.

Lev and Sunder (1979) suggest that one could use the mean, maximum, or minimum of the entire field. This approach again is fraught with difficulties.

Companies operate in accordance with certain policies which vary between accounting periods as agreed by the directors at Board meetings. Having said that, accounting policies are prepared in the interest of the company and therefore vary according to the issues facing the company at a particular point in time. To apply the minimum or maximum of the entire field would be totally misleading.

It has been suggested by Alici and Gifford (1995) that where the field contains categorical data for different periods and there is a missing value in the category of one period, another category should be created. It will be inappropriate to create another category because two categories may represent separate performance indicators. Further, the danger with this approach is that this could blur the difference between a failed firm and a healthy firm. Having said all that, it is fraudulent and illegal to create another category because financial investors could rely on a supposedly created category which could produce dire consequences.

Lee and Wu (1988) suggest that if the field contains numerical data, one should create an enumerated field to mark records with the original field missing. To do this would disregard the characteristics of the underlying stochastic processes generating the missing value. For example, annual depreciation affects the value of fixed assets as disclosed in financial statements. If this underlying information is disregarded when dealing with missing values, the results obtained may be erroneous. Handling missing values in financial statements is not simple and cannot be solved by the simple rule of substitution. One matter that should be borne in mind constantly when handling missing data is that the more the accurate the values introduced, the better the resulting network.

## 4.2 Handling Financial Outliers

Perhaps the greatest difficulty in pre-processing financial data for neural network inputs is the widespread existence of outliers in financial ratios. Outliers can be regarded as one of the main reasons for the absence of normality in financial ratios. Up to now, no published accounting study has attempted to address the issue of multivariate financial outliers. This section of the paper will address this phenomenon.

Deaking (1976) suggests that outliers in financial ratios should be deleted. This approach may give ground for concern. Lack of fit of financial ratio data to multivariate normality is amplified when some observations in financial data are multivariate outliers. In contrast to outliers in univariate analysis, multivariate financial outliers may consist of data values that do not simply spin out at the ends of univariate distributions. Having said that, multivariate data values may also be discordant (conflicting) because of subtle, unexpected patterns of values on subsets of financial variables. Furthermore, multivariate financial outliers have disproportionate influences on parameter estimates and on the predictions of corporate bankruptcy (1994). To delete them will not solve the problem but add more to the problems of multivariate nonnormality in financial data analysis. Knowledge from practice would suggest that the basic characteristics of the outliers should be determined and compared to the entire population in the data set. It may be that there are some irreconcilable factors affecting the two groups. It may also be that the outliers represent a completely different industrial sector, or at worst, the data should not have been there in the first place. The reasons for the existence of the outliers should therefore be examined and reconciled with the entire population. This is important because it is possible that several variables, when examined individually, may be univariate normal and yet their multivariate distribution is nonnormal. If any reconciliation is not possible, then the procedure for sampling and selection of data must be revisited and possibly revised. Regrettably, univariate outlier identification and deletion procedures ensure neither multivariate normality nor equal covariance matrices.

One particular statistical technique for handling outliers is known as winsorizing. Winsorizing is where the extreme values for some financial ratios are replaced by substitute values (1988). This technique presents the greatest dangers. Investors invest in companies to win or lose on actual values of financial ratios and not substitute values. Replacing extreme values with substitute values may produce misclassifications. Moreover, univariate winsorizing procedures are intended to induce reasonable approximations of multivariate normality. The examination of multivariate outliers and multivariate distributional properties has been neglected in many analysis of the cross-sectional distributions of financial ratios, and they deserve further study.

### 4.3 Handling Hidden Data.

Hidden data occurs when the directors of a company have decided to withhold confidential information about their firm's strengths and weaknesses. This could be done in order to hide information about their imminent collapse or simply to preserve the interests of the company so as to avoid a take over raid from competitor large firms. A company is legally allowed to do this if to do otherwise would bring about a predator and victim situation and also, to protect the interests of the company. Knowledge from experience in handling this kind of problem is to obtain descriptive information about the company which is contained in the financial statements known as internal sources together with external information deduced from reading economic reports available in the public domain. One source of information is the Financial Times. Once this descriptive information has been obtained, it can be analysed as symbolic data and then one can use a one-of-N-transformation as numeric format for neural inputs. The characteristics of hidden data themselves are multivariate nonnormal which may escape undetected due to the masking effects of other extreme observations. Care should therefore be taken when using these symbolic data or their transformation as numeric input to neural networks.

# 5. Conclusion

Many of methodological requirements of bankruptcy prediction models have been addressed in this study. Researchers can improve on the validity of their analyses by matching samples of failing and healthy firms by size and industry and also, by taking care that economic theories are constantly applied in their empirical research in financial prediction. The properties of accounting numbers do not permit any models with few parameters to capture the irregularities in financial ratios due to their stochastic nature. The complexities surrounding corporate failure do not permit few parameters to be examined and analysed as input representations to neural network. There has been less consistency in the selection of financial variables because of lack sound economic foundation in financial modelling. This study proposes that there should be a consistent pattern in financial modelling approaches by applying economic theories in data sampling and selection before selecting financial parameters as input representations to artificial neural networks.

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# Predicting Corporate Bankruptcy Using Modular Neural Networks

M.L. Nasir, R.I. John, S.C. Bennett.
Centre for Computational Intelligence
De Montfort University
The Gateway, Leicester LE1 9BH, United Kingdom
and
D.M. Russell.
Department of Accounting and Finance Leicester Business School
De Montfort University The Gateway Leicester LE1 9BH.

Email: mln@dmu.ac.uk

## ABSTRACT

This paper reports on the use of modular neural networks for predicting corporate bankruptcy. We obtained our financial, as well as, political and economic data from The London Stock Exchange, JORDANS financial database of major British public and private companies, and the Bank of England. In the past, various statistical techniques, such as univariate and multivariate discriminant analysis have been used in the modelling of corporate bankruptcy prediction. We use domain expert knowledge to select, and organise data in the modular neural network architecture constructed for this study. There are three sub-networks representing the periods, 1994, 1995, and 1996. Each sub-network is made of five adjacent networks representing the Balance Sheet network, the Profit and Loss network, the Financial Summary network, the Key Financial Ratios network, and the Economic and Political factors network. These adjacent networks although coupled but not linked at the input level represents five facets of failure in predicting corporate bankruptcy. The training sets represents data for 2500 companies selected randomly from a population of 270,000 sample. The trained neural network will access 435,000 data records before making a prediction for the particular company. The results obtained shows that neural networks outperform statistical techniques in modelling corporate failure prediction.

## INRODUCTION

Predicting corporate bankruptcy can be regarded as a pattern recognition problem because companies' activities change over time. It is therefore necessary for these temporal tendencies to be captured if a meaningful approach is to be undertaken. Indeed, the ability of neural networks to discern patterns of irregularity and or ambiguity in the data submitted to them makes learning algorithms suitable for corporate failure prediction. However, the studies conducted by Odom and Sharda (1990), Alici (1995) have used one year prior to failure data to capture temporal tendencies in financial data (Nasir et. al., 1999). Having said that, it appears that the general tendency in corporate failure prediction is that neural networks are used extensively to learn and predict time series, but most of the approaches aim only at single point-predictions. When the time series is noisy as they usually occur with financial data, however, single point predictions themselves are not very meaningful unless at least their confidence intervals can be predicted as well. The only satisfactory approach in the general case is therefore to predict the entire time series. The paper show that alternative neural network architecture exist for measuring temporal tendencies in financial data.

### Previous Research

Previous studies in using univariate and multivariate discriminant analysis have already been mentioned and evaluated in Nasir et. al., 1996; 1997; 1998; 1999; 2000. Previous works in using neural networks will be narrated in this section for completeness.

Among the first neural network failure studies was that of Odom and Sharda (1990). They adopted the work of Altman (1968) by employing the same number of financial ratios as described in chapter 2. The study selected a sample of 65 failed companies and 64 non-failed US companies. The training set comprised 38 failed and 36 non-failed companies, the reminder being used as validation sample. A three-layer neural network was created with five hidden nodes. Convergence was achieved after 24 hours and 191,400 iterations. The neural network correctly identified all the failed and non-failed companies in the training sample, compared to a successful classification rate of 86% for a benchmark discriminant model. Both models were then tested on a hold out sample using prior probability of failure estimates of 50:50, 20:80 and 10:90. The neural network model correctly classified bankrupt companies in 78% or more occasions under all three-probability priors. However, for the non-failed companies, the correct classification is 79% for the network and 89% for the discriminant model.

The study by Fletcher and Gross (1993) used backpropagation neural network to identify corporate bankruptcies from a sample of 18 matched pairs of companies. Employing three accounting ratios as the explanatory variables, they investigated the impact on the performance of their neural network models of the number of neurons in the hidden layer. The results shows that models with between 3 and 7 hidden nodes were better able to discriminate than comparable to logit models. However, the 82% correct prediction rate reported that was claimed achieved without adjusting for sampling bias, which suggests that none of the models would be very helpful in practice anyway.

Coats and Fant (1993) identify 94 manufacturing companies that are known to be bankrupt over the period 1970-1989. Against these they used 188 non-failed listed companies, almost half of which were not in the manufacturing sector. The training and test sets comprised 47 failed and 94 non-failed companies. As in Odom and Sharda's study, the variables in the training set data were five financial ratios used in the Altman's 1968 discriminant study. They claimed the model achieved 80% classification after 1400 training cycles.

Wilson and Sharda (1994) used a training sample of 100 companies, which covers both bankrupt and non-bankrupt companies. The model was derived from one year prior to failure data. The authors used the same number of financial ratios (input variables) as the Altman (1968) study. The variables selected were five. The training algorithm used was backpropagation with one hidden and output layer. It was claimed in this paper that the network model was able to obtain a 100% classification of the training set and when submitting the test set, the network model achieved 73% accuracy in both cases.

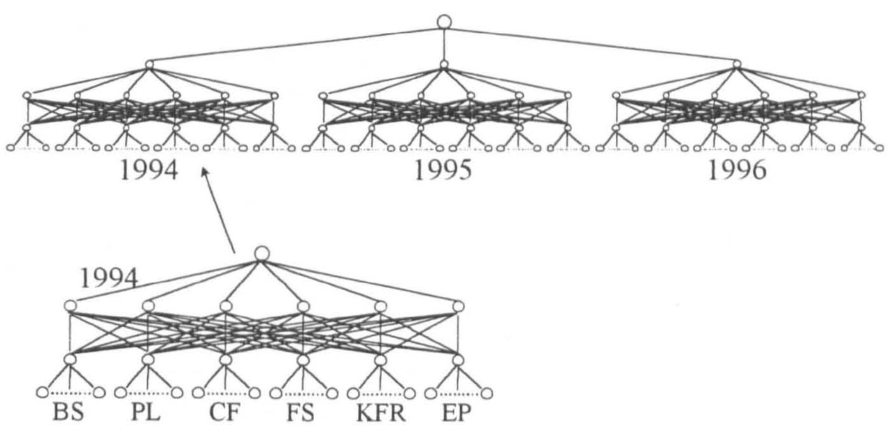
Tam (1991) study developed a backpropagation model to identify bankrupt companies. This was constructed on a sample of 59 failed matched with 59 non-failed companies. The financial ratios selected were based on Altman's 1968 study. However, the misclassification errors were much higher than that reported by Altman.

Salchenbeger et. al., (1991) applied the neural network procedure to discriminate between 100 US companies which failed between 1986-1987 and a similar number of non-failed matched pairs. Applying five financial ratios, the neural network model consistently outperformed the Altman's 1968 model. Moreover, when testing against a situation where the proportion of non-failed companies to failed was more realistic, the neural network still performed tolerably well, although misclassification error for failing companies were much higher.

Wilson et. al., (1995) bankruptcy study cover a sample of 112 companies. These comprising 40 failed, 32 distressed, and 40 non-failed companies. A total number of 18 explanatory financial variables were selected for the experiment. The topology of the network comprised an input layer, hidden layer, and an output layer. Between 30-40 epochs were used before convergence was achieved after 100,000 training iterations. The model did extremely well when tested on the training sample but far less well when tested on the hold out sample. The misclassification error was far higher with respect to failed companies.

Alici (1995) data set covers two main groups, the failed and healthy firms. The selections of 46 failed companies were matched with 46 healthy companies. As for the external ability of the derived models, 310 failed and 280 non-failed company cases were randomly taken from the MicroEXTAT data base covering all industries and hold out samples were conducted over five years for already failed companies between 1987-1992. He selected 28 financial variables by employing PCA and profile analysis to characterise those variables. He trained his network by using the Self-Organising Feature Maps (SOM) as a benchmark against his PCA model. A "skeletonisation" procedure was employed in order to establish the number of financial variables and optimum network structure. The prediction results from the model achieved 68% accuracy. It was also claimed that SOM could be used to group financial ratios before input into neural networks.

**Our Methodology: The Alternative Neural Network Architecture**




**Sample Determination**

Data Sources:
a) The London Stock Exchange
b) Jordans Financial Database
c) The Bank of England
d) The Institute of Directors

Total Sample Size: 270,000 major public and private British companies

Reduction Process:
a) Exclude new firms
b) Exclude small firms
c) Exclude firms by Turnover
d) Exclude firms with small assets
e) Exclude overseas subsidiaries

Selection Criteria:
a) Define period of study
b) Define Bankrupt company
c) Define Non-Bankrupt company
d) Define "mates" category
e) Final selection: 2500 companies

Select Input Variables for:

| | | | | |
|---|---|---|---|---|
| Balance Sheet Network | (10) | 1994 | 1995 | 1996 |
| Profit & Loss Network | (8) | 1994 | 1995 | 1996 |
| Cash Flow Network | (10) | 1994 | 1995 | 1996 |
| Financial Summary | (6) | 1994 | 1995 | 1996 |
| Key Financial Ratios | (20) | 1994 | 1995 | 1996 |

**Results**

| | |
|---|---|
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Sigmoid |
| LEARNING RULE | Delta |
| EPOCH SIZE | 56 |
| ITERATIONS | 150000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.4 | 0.3 | 0.2 | 0.1 | 0.0 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 93 | % bankrupt wrong | 7 | % bankrupt don't know | 0 |
| % Healthy right | 72 | % healthy wrong | 26 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

No of Bankrupt 72
No of Healthy 328

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 82 | % bankrupt wrong | 3 | % bankrupt don't know | 15 |
| % Healthy right | 46 | % healthy wrong | 8 | % healthy don't know | 47 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 73 | % bankrupt wrong | 3 | % bankrupt don't know | 24 |
| % Healthy right | 34 | % healthy wrong | 2 | % healthy don't know | 63 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 63 | % bankrupt wrong | 3 | % bankrupt don't know | 35 |
| % Healthy right | 23 | % healthy wrong | 1 | % healthy don't know | 76 |

## Discussion of Results

The results generated represent training cases for 2500 companies. The input measurements used were 58, representing the Cash Flow network, Profit and Loss Statement network, Balance Sheet Network, Key Financial Ratios Network, Financial Summary Network, and Economic and Political factors Network. When evaluating the predictive capability of the neural network, a testing threshold, similar to the training tolerance, is specified. This testing threshold identifies how stringent the allowable variation in output neurons can be when predicting the status of the companies in the training set. In this study, four testing thresholds were used; 0.50 and 0.50, 0.20 and 0.80, 0.10 and 0.90 and 0.05 and 0.95. This basis was used for correct and incorrect classifications for the neural network model. When checking the neuron output for both criteria, the network achieved the following results:

As revealed in Table 1 above, there were 72 bankrupt companies and 328 healthy companies. Using the 0.1 and 0.90 criteria, the network correctly classified 73% of bankrupt companies and returning 24% as don't knows. The network misclassified 3% of bankrupt companies. Looking at the healthy companies, the network correctly classified 34% of healthy companies and returning 63% as 'don't know'. The network misclassified 2% of bankrupt companies. Using criteria that are more stringent: 0.05 and 0.95, the network correctly classified 63% of bankrupt companies and returning 35% as 'don't know'. The network misclassified 3% of bankrupt companies. The network correctly classified 23% of healthy companies and returning 76% as 'don't know'. The network misclassified 1% of healthy companies.

## Conclusions

A priori reasoning suggests that it ought to be very complex and quite difficult to devise corporate failure identification models for listed and unlisted companies which will consistently be able to detect future bankruptcies. Yet despite this, the fact is that it is often possible to achieve this if the model has been developed properly. We propose that domain expert knowledge is particularly useful in modelling the application of corporate failure prediction.

A close examination of previous empirical work suggests that since 1932 academics have spent too much time in developing statistical procedures to numerous different types of independent explanatory variables, but for the most part without greatly improving discriminatory power. In addition, a large number of simple models of neural networks have been developed to predict the next time step. The former approach completely suffers from the normality assumptions and the latter is totally inappropriate when measuring temporal tendencies in financial data. The properties of accounting numbers do not permit any models with few parameters to capture the irregularities in financial data due to their stochastic nature.

We are therefore continuing our effort in trying to improve the network reported in this study.

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# HANDLING NON-CONVERGENCE IN TIME VARYING NEURAL NETWORKS

M.L. NASIR, R.I. JOHN, S.C. BENNETT.
Centre for Computational Intelligence
De Montfort University
The Gateway, Leicester LE1 9BH, United Kingdom
Email: **mln@dmu.ac.uk**

D.M. RUSSELL.
Department of Accounting and Finance Leicester Business School
De Montfort University The Gateway Leicester LE1 9BH.

## ABSTRACT

We describe a training algorithm based on inter-connected neural networks for the predictions of corporate bankruptcy. The proposed methodology seeks to optimise the generalisation performance of feed-forward modular networks by gradually increasing the number of training iterations, and adjusting parameter values, until convergence was achieved. We show that during the initial learning process, the network goes through stages in which the improvement of the response was extremely slow and results obtained very disappointing. However, these periods of stagnation are much shorter as training runs increase and parameter values adjusted accordingly. This paper presents the best solution after carrying out sixty-five network runs.

Key Words: Neural Networks, Convergence, Forecasting, Learning, Development Issues.

**Introduction**

Generalisation is the term used to refer to the ability of neural networks to produce correct response when tested against unseen data sets. It has been shown in Hoptroff et. al., (1991) that to achieve significant levels of predictive validity, the proportion of correct positive predictions (classifications of bankrupt and non-bankrupt for example) must exceed the base rate of 50 per cent. Denker and Wittner, (1987) suggest that, in order to distinguish between a 'good' and a 'bad' network, a more stringent threshold of 5% and 95% should be considered. This means, a bankrupt company prediction must be within the range $\leq 0.05$ and the non-bankrupt $\geq 0.95$. If the network output is say, 0.0485 for a bankrupt company, this will be taken as correct classification using the stringent criteria. However, if the network output is say, 0.8526 for a healthy company, then using our criteria, this is regarded as a 'don't know' classification. Our criteria show that it is possible to establish a clear-cut polarisation when interpreting neural network results. Odom and Sharda (1990) bankruptcy study proposed that 50:50 criterion should be used when interpreting neural network results. The main concern with their proposal is that the network will simply push its scale of predictions to the middle without a clear-cut polarisation. We believe that the more stringent the criteria, the more reliable the network model especially when considering the bankruptcy phenomenon. Mozer, (1993) and Moody, (1992) argue that a model that generalises very well using $\geq 0.05$ and $\geq 0.95$ (our criteria) is a very good network. Since we have adopted this stringent criterion, the implication is that all sorts of convergence problems would arise. This paper shows how we were able to achieve convergence in these particular difficult and complex circumstances.

## PREVIOUS RESEARCH

We present our investigative study on methods to improve backpropagation learning and optimisation capability of neural networks. Several techniques have been put forward to speed up learning. Hush and Salas (1988) proposed several approaches such as the variations in learning parameters; e.g. momentum rate, switching between alternative cost functions instead of relying on the standard quadratic error function. Farmer and Sidorowich 1988, argue for the adaptation of the learning parameters.

Rumelhart (1986) proposed that at the initial outset of network training runs, the first network should be rigorously scrutinised for any surplus processing units. According to Rumelhart, the aim of this exercise is to find out whether there are some units that are deemed, in some sense, redundant. However, this proposal could lead to a shrink network especially where the input variables had been selected based on some method rules and a reduction in the number of input variables would make the model impracticable (Groot and Wurtz, (1991). For example, variables could have been selected based on domain knowledge; any reduction in the variables therefore makes the model less practicable.

Mozer and Smolensky, (1990) identified "skeletonisation" technique as a way of improving complex and difficult backpropagation neural networks. This technique had been described as follows:

- Train a fully connected network to a level where an acceptable level of error is produced for every training pattern.
- Compute the relevance for each unit in the network.
- Eliminate from the network the unit with the smallest relevance value.
- Repeat the above steps a set number of times and halt at a pre-determined stopping point.

Although Sprecher, (1965) argued that a network with a smaller number of units might have fared better than the network with larger units. However, we have the following reservations that have been previously observed in Nasir et. al., 1998; 1999; 2000.

1. Units vary in their functional importance for solving any particular problem and since this is always the case, there is the possibility that important units may be removed.
2. Those input units representing exceptional cases in the model (probably critical for good generalisation) might have to be deleted.
3. The upshot of this would have been a smaller network, but one which no longer solve the original problem at hand. This appears to point to a rather profound problem with the skeletonisation technique.

However, we propose that a good way of discovering whether a unit is functionally important is to monitor what happens if the unit and its connections are removed. The relevance of a unit can then be defined in terms of the difference in the network's performance when the unit is included as compared to when the unit is removed. If this discrepancy is large then the unit is deemed functionally useful and it should be re-introduced and retained. However, if the discrepancy is small, then the unit's usefulness is questionable and it might then be removed. The most important point to remember here is that small discrepancy sometimes contributes noise and promotes good generalisation capability (Hoptroff, 1993). The study conducted by Frean, (1989) appear to have introduced a reasonably principled means for "pruning" units automatically, however, the study has failed to provide any guidelines for when to halt the procedure. The other concern is that the approach may risk overfitting the data. When this the case, the network will certainly have so much power that it will simply memorise the data sets and becomes less effective in application (Karnin, 1990; Shepanski, 1988; Le Cun, 1989; Carter, 1987).

Although convergence problems abound in deciding a critical level of relevance, Hirose et. al., (1991) proposed limiting the number of hidden nodes in order to improve generalisation capability. This suggestion was taken up by the study by varying the number of hidden nodes in the 65 network runs. However, we encountered two fundamental problems.

- Underneath the noise, the target function of which the data sets lie has a certain form. Since the number of hidden nodes is rigidly controlled, the network was misled by noise into producing a form that is too complex than the target function.

- Each weight in the network is a parameter that adds to the capacity of the network. The number of weights determines the degrees of freedom with which the network can fit the data. This is particularly daunting where, as in our case, there is a large data sample, because the number of weights in the network is a function of the number of nodes it has. Since the number of output nodes in a network is generally determined by the nature of the problem, by controlling or limiting the number of hidden units can produce all sorts of problems as we find out. The derivative errors in each network start to increase instead of reducing towards the zero mark.

The study conducted by Ooyen and Nienhus, (1991) proposed a modification to the backpropagation method. The modification consists of a simple change in the total error-of-performance function that is to be minimised by the algorithm. It was suggested that learning would improve and thus promote convergence. We took this opportunity and tried this proposal. We experimented with several network runs starting from different initialisations, and random weights jogging. The same initialisations were used for both the modified method as suggested by Ooyen and Nienhus, (1991) and the original method with no modifications to the error function (Sperduti and Starita, 1992). Although, in principle, the suggestion appears to be self-limiting, no conditions on when to stop training was discussed or examined. In adopting this supposedly unique approach, we find out that as the network goes through its learning process, improvement of the response was extremely slow. It was noted later that this delay of the convergence is caused by the derivative of the activation function. These periods of stagnation became longer than expected and training was abandoned.

Perhaps the most well known approach of improving backpropagation network is that described by Silva and Amelda, (1990). They proposed that the initial network should contain a set of input units, a set of output units, and interconnections between the input and output units with no hidden layers. The single layered network should be trained until performance is within some pre-defined criterion. Typically, the network would be trained with certain number of epochs. For each epoch, the set of input patterns should be randomised. This should be repeated a number of times until convergence were achieved and then the network performance is assessed. If the network was now performing within an acceptable limit, training should cease. However, if the network's performance is judged not acceptable, then a hidden layer "candidate" unit should be introduced. It had been demonstrated in Chauvin, (1989) that this method results in faster learning times and that it eventuates in small network that generalise very well. It was claimed that the faster learning times, in part, arose from the process of freezing the weights and only training one hidden layer of connection at a time. When trying this approach, three problems became apparent.

- Increasing the number of epochs using a PC can be painstaking. The training process is bound to become extremely slow and sometimes ineffectual.
- Second, this is a cascade-correlation method where there is no backward propagation of an error signal through intermediate layers of hidden units; only one layer of connections is trained for each step in the algorithm.
- Third, generalisation ability was seriously affected since the errors were not backpropagated. The cascade-correlation procedure produced a straightforward linear network. However, bankruptcy problem is non-linear (Farmer and Sidorowich, 1988).

Weigend et. al. (1991) suggested how adaptation of the steepness of the sigmoid functions during learning could improve convergence. The adaptation method is obtained by simulating a standard network with fixed sigmoids and a learning rule whose main component is gradient descent with adaptive learning parameters. The basic idea here is the introduction of variation on steepness parameters so that the architecture can be optimised with respect to the number of units presented to the network. Optimisation of units is then obtained by introducing a tendency to decay to zero in the steepness values and comparing this with the sensitivity of the input units. In this way, according to Mozer, (1993), units, which are not useful in implementing the target function, can be removed after a given transformation of the biases of the network. We adopted this approach, however, our first network got stuck in local minima for a rather long time. Although we were aware of the methods for pushing neural networks out of local minima, it was rather difficult to set the decay rate in such a way as to obtain good results without risking slowing down the convergence speed of the learning or causing all the steepness parameters to be null. It became even more particularly difficult to jog weights, or change parameters as suggested by Jacobs, (1988). So, we decided to set the initial distribution of the steepness parameters with low hidden units with a significant steepness value; and the input units initialised with small steepness value. This produced one further problem. Rather than promoting a clear differentiation between steepness value in the hidden units and the input units, it was totally otherwise. We thought adopting this approach would allow us to obtain a decay that can inhibit the activity in the small hidden units that are needed to implement the target function. However, if the size of the hidden layer is too small for the real needs of the target function, the learning on the steepness value will automatically recruit new hidden unit by increasing its steepness value.

We performed more experiments by adding a momentum to the weights change; using various levels of epoch size; varying network parameters with different transfer functions and learning rules. The learning became slower than expected, and it would mean reducing the original input units significantly for any meaningful results to be obtained. The resulting procedure thus compromises between speed of learning, input units, and network effectiveness. The approach of Jacobs, (1988) was not satisfactory.

## DESCRIPTION OF ARCHITECTURE

The neural network topology is shown in Figure 1 below. Our preferred model is made of a series of inter-connected networks each connected to its immediate neighbours. Thus the hidden layer in 1995 receives additional input from the 1994 network and the hidden of 1996 receives additional input from the 1995 network and provide an encoding of a three year period. There is a feedforward connection between the input units to the first hidden layer and full connection between the two hidden layers. High level topology captures temporal nature of data. Low level (i.e. connection between input units to the first hidden layer) topology of sub-networks uses domain knowledge.

We conducted many network runs, however, the results and parameter values determined for each run cannot be produced here for lack of space.

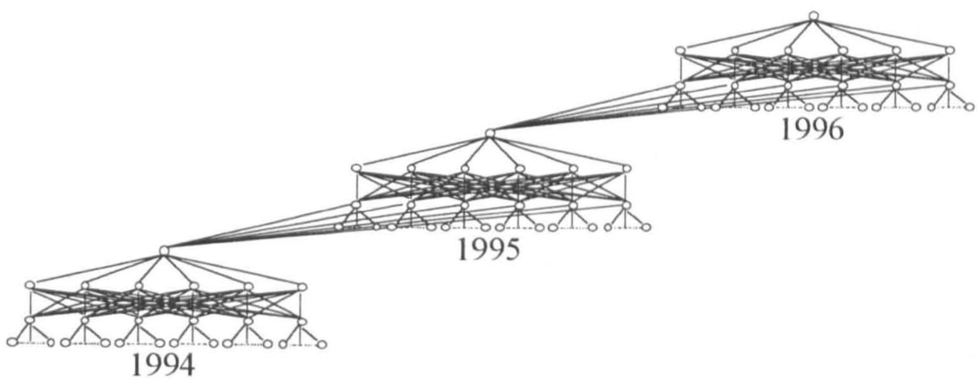


**Figure: 1 Building in Time (inter-connected) sub-networks**

## HANDLING NON-CONVERGENCE

Few network runs conducted show high cases of 'don't knows' and some misclassifications when using our stringent criteria. Therefore, efforts had to be made to deal with this particular problem. -

What follows are the steps taken to improve upon the results from our initial network runs.

**Step 1:** Network pruning.

This study looked at each of the processing elements in the input layer. The reason for this is to find out whether all of the connections to a particular input are very small. If they are found small, the input processing will be disabled (i.e. set to zero). Later, that particular input field will be removed from the transformation program. This approach caused a lot of concern because it will mean that the number of network inputs will be reduced. It was decided not to go down this route. The objective of this study is to force the network to train with the pre-determined input variables that have been selected using domain expert knowledge. Pruning the network may lead to a small network and may be less effective.

**Step 2:** Examine network connections rigorously.

To examine the connections from the input layer, it is necessary to look at each of the processing elements and its input layer for connectivity problems. This was done using Hinton diagram. This action caused the Global Learning Rule (Network Parameters) to be active. Before any changes can take place, the training and test data must be refined; the data scaling must be revisited; and then, every single weight on each connection checked for irregularity and or ambiguity.

**Step 3:** Jog weights on the connections.

Jogging weights for all connections help to push the network out of its current state. The current state of the network could be poor performance or local minima (Coats and Fant, 1992). Jogging cause weights to be multiplicatively post normalised as appropriate (Lapedes and Farber, 1988). This study used the Gaussian distribution to set the high and low weight limits within +/-1 sigma. The Gaussian distribution helps to identify the number of weights and its associated connections that ought to be investigated. Recall this action will not necessarily shrink our network but improve upon its ability to generalise effectively. This approach attempts to minimise network complexity while enabling our effort to retain the original input units to the network.

**Step 4:** Increase Training Iterations

Training counts were randomly increased or decreased between runs and this depends on the values of parameter attached to each attempted run. In addition, the choice of training counts depended on the nature of data, size of data and its organisation in the network. At this point, we started noticing some marked improvements in the generalisation capability of the network. We decided to continue training by simply varying all the network parameters and increasing the training iterations.

**Step 5:** Switch between Transfer Functions

The choice of a transfer function is determined by the exact type of data and what the network is expected to learn (Becker and Le Cun, 1989). The important observation in this study was to switch between transfer functions at different runs. In a number of studies, (see, Ash, 1989; Le Cun, 1988; Werbos, 1988; White, 1989) it had been suggested that, if the problem involves learning about clear cut "deviations" from the average, hyperbolic tangent works best. For example, Odom and Sharda, (1990) have compared the prediction capabilities of sigmoid transfer function with hyperbolic tangent. Using a training set of 83 bankrupt companies, the network achieved 86.78% accuracy rate when employing the hyperbolic tangent. This is compared to 56.45% when using sigmoid transfer function. Williams and Zipser, (1989) argue that, if the problem involves learning about "average" behaviour, sigmoid transfer function works best. Weigend and Gershenfeld (1993) proposed that, if the objective is to learn to pick out "exceptional" situations, hyperbolic tangent work best. We achieved convergence by fixing the transfer function at (hyperbolic TanH) and the learning rule at (Norm-Cum Delta-Bar Rule) and subsequently; vary other parameter values (including network biases). These actions caused major improvements. This is a particular daunting aspect of neural networks training, knowing what to do for the right circumstances (Widrow, 1962; Nasir et. al., 1997).

**Step 6:** Revisit network development issues

Many parameters and decisions that were involved in developing model had to be revisited again. Table 6.1 illustrates some of those extensive reviews.

- Confirm the training and test sets.
- Confirm method of transferring data into suitable input values.
- Determine the number of hidden layers.
- Determine the initial input weights.
- Select a propagation rule.
- Select an activation rule.
- Check the pattern of connectivity again.
- Revisit the network size:

a) Check the number of processing units in the hidden layer.
b) Check the number of processing units (PE) in the hidden layers.
c) Check the number of processing units (PE) in the output layer.

## RESULTS

This subsection presents the best parameter values and the results produced. Recall that this position was obtained after carrying o 65 'replicate' network runs. The remaining results of runs for this model can be obtained from the author directly by email.

| | |
|---|---|
| RUN NO: | 64 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | TanH |
| LEARNING RULE | Norm-Cum-Delta |
| EPOCH SIZE | 100 |
| ITERATIONS | 1000000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 150000 | 250000 | 300000 | 100000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

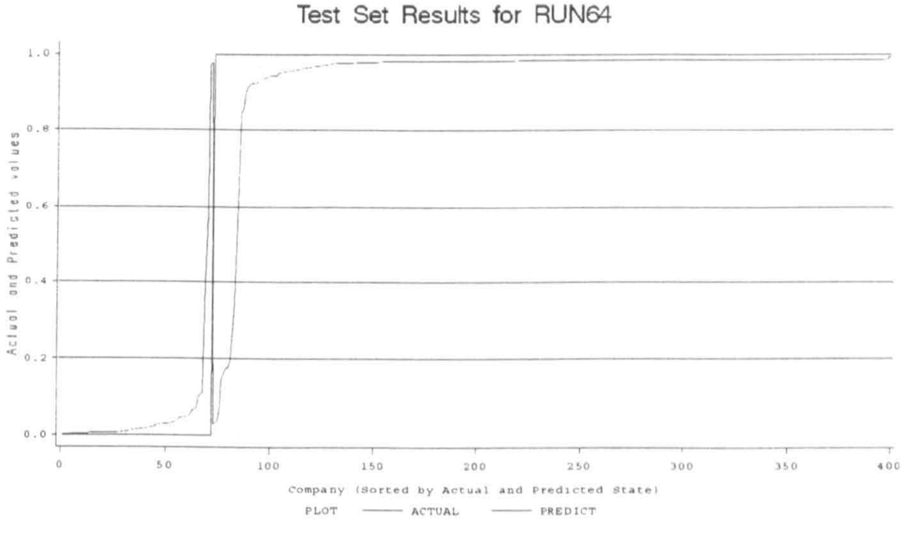


Fig: 2: Best Solution (Network RUN64)

## DISCUSSION

The input units in the above network represented data values for various financial, economic and political data. Two testing thresholds were used to test the predictive capability of the network. These testing thresholds identify how stringent the allowable variation in output neurons can be when predicting the status of both categories (i.e. bankrupt and non-bankrupt) in the test set. Using the 0.5 and 0.5 basis, the network achieved correct (97%) classifications for the non-bankrupt, and correct (96%) classifications for the bankrupt companies.

Although the network did not return any company in both categories as 'don't knows', however, it misclassified 3% of non-bankrupt companies as bankrupt and 4% of bankrupt companies as non-bankrupt. The former is known as type 1 error and the latter is known as type 2 error. Using our preferred (stringent) criteria; i.e. 0.05 and 0.95, the network achieved correct (91%) classifications for the non-bankrupt companies and 81% correct classifications for the bankrupt companies. Although the network did return 9% of non-bankrupt and 13% of bankrupt cases as don't knows, however, it misclassified 1% of non-bankrupt companies as bankrupt and 3% of bankrupt companies as non-bankrupt. As mentioned earlier, 65 network runs were replicated before satisfactory conclusions were reached.

## SUMMARY

In this paper, we have demonstrated that increasing the number of training iterations, and adjusting parameter values at different levels in the Global Learning Schedule can improve the generalisation performance of feed forward modular neural networks. The modification amounts to selecting a fixed transfer function; the hyperbolic tangent, and using the Norm-Cum Delta-Bar-Rule as the learning Rule. We also vary other network parameter values (including network biases). We adopted the total error function that is to be minimised by the algorithm. Consequently, the error signal produced by the output neuron is now directly proportional to the difference between the actual activation of the unit and its target value. This produced marked improvements in results obtained. Therefore, when a strong error signal is produced, the output unit approaches the value of 0 or 1.

With the first network run, there are periods of stagnation, during which the performance of the network improves very slowly. Closely studying the behaviour of the network revealed that weights on the connections were moving away from their target values and as such becomes stuck in local minima. Competition was promoted by jogging the weights on each connection, switching between different transfer and error functions, and fixing the epoch to 100 level. Since the signal that is propagated backward is very small, the performance of the network hardly improves: a plateau of error arises. The network position was improved by using 'trial and error process' to vary parameter values. During this process, the total error is hardly changing until a certain threshold is reached after which the network changes exponentially.

Convergence was achieved after carrying out sixty-five network runs. The transfer function was fixed at the hyperbolic tangent whilst varying other parameter values, and increasing the number of training iterations at the same time. The trial and error process had been very fruitful. Our best network successfully predicted over 95% on average in all (unseen) test cases. The level of error reported in our study is typical especially with the level of network complexity.

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# Selecting the Neural Network Topology for Predicting Corporate Bankruptcy

M.L. Nasir, R.I. John, S.C. Bennett.
Centre for Computational Intelligence
De Montfort University
The Gateway, Leicester LE1 9BH, United Kingdom
and
D.M. Russell.
Department of Accounting and Finance Leicester Business School
De Montfort University The Gateway Leicester LE1 9BH.

email: mln@dmu.ac.uk

## ABSTRACT

Neural Network topology selection refers to a systematic procedure for selecting between competing models. Naturally, it is regarded as a key aspect in optimisation and replicability of neural network performance. When constructing neural network topologies, it is necessary to determine from the outset the general taxonomy of the neural network architectures to be constructed. The taxonomy considered in this study is the general taxonomy of time-varying patterns which subsumes many existing architectures in the literature and points to several promising neural network architectures that have yet to be examined. The context of the problem is that choosing the right neural network topology for use in a particular domain such as corporate bankruptcy prediction with optimum generalisation performance is not, in any case, a trivial problem. The results of experiments presented in this paper would serve as baseline against which to select between two competing architectures.

## 1. INTRODUCTION

The selection of a specific neural network topology for use in a particular domain such as corporate bankruptcy prediction involves the daunting task of constructing a large number of neural network topologies with different structures and parameter values before arriving at an acceptable model. The task is to choose a functional neural network from a number of possibly competing alternatives, and to estimate the parameters in a manner that satisfies a fitness criterion. The context of the problem is that there are no fixed rules involved in determining the appropriate architecture or its parameter values. The trial and error process can be tedious and time consuming and yet, this process is particularly significant in deriving a good model. This paper addresses this important phenomenon.

Lippmann (1987) argues that over the years of development of the neural network field an impressive number of model selection procedures have been proposed. The cross-fertilisation deferent discipline has been also considerable. Choosing the right neural network topology to solve a particular problem with optimum generalisation performance is not, in any case, a trivial problem. The unpredictable interactions of numerous design considerations would depend largely on the network methodology chosen. The success or failure of the methodology chosen would have a direct consequence on the final neural network topology. This paper attempts to give a categorisation of the different procedures along with some characteristic examples.

## 2 NEURAL NETWORK TAXONOMY

The first and obvious thing to do is to determine the general taxonomy of the neural network architectures to be constructed. However in particular, the general taxonomy of temporal processing architectures subsumes much existing architecture in literature and points to other neural network architectures discussed in literature. The determinations of the general taxonomy of neural network architectures for financial time series prediction can be very difficult (Weigend et. al., 1991; Lapedes and Farber, 1987). Temporal processing is a particularly challenging problem because conventional neural network architectures and algorithms are not well suited for patterns that vary over time (Wang et. al., 1994). The prototypical use of neural networks is in structural pattern recognition. In this case, a collection of features (e.g. assets, liabilities, or otherwise) is presented to a network and the network must categorise the input feature pattern as belonging to one or more classes. For example, a network might be trained to classify companies based on a set of attributes describing financial indicators such as "positive," "negative," or "no change"; or a network can be trained to recognise failure indicators in the financial statements of current operating companies. In these circumstances, the network is presented with all the relevant information simultaneously. In contrast to the above, temporal pattern recognition involves processing patterns that evolve over time. So, the appropriate response at a particular point in time depends on two situations. The first is the current input and the second is potentially on all previous inputs.

The basic framework for a temporal prediction network is to have data (in this case financial) quantized into three discrete steps, a sensible assumption, since financial time series data are intrinsically discrete, and continuos series can be sampled at a fixed interval. Prediction involves two conceptually distinct components. The first is to construct a neural network that will act as short-term memory that retains aspects of the input sequence relevant to making predictions. The second makes a prediction based on the short-term memory. Applying this taxonomy to a neural network framework, the predictor will always be a feedforward component of the network, while the short-term memory will often have internal recurrent (historical) connections. The short-term memory network would be the output of the previous network feeding its output to the hidden layers of the current network. Specifying the number of hidden layers and units, the pattern of connectivity among units, and the activation dynamics of the units are issues necessary to be considered when determining the taxonomy of neural network architectures for temporal processing.

## 3 SELECTING NEURAL NETWOK TOPOLOGY

Although statistical procedures has been largely ignored in this study because of their failure to deal accurately with temporal tendencies (Husmeir and Taylor, 1997). The only satisfactory approach in applying statistical techniques to neural network derivations, is in the general case, when neural networks are trained to predict the next time step (Husmeir and Taylor, 1997; Allen and Taylor, 1994; Bishop, 1995; Weigend and Srivastava, 1995; le Cun (1989). Swinger, (1996) conducted a study on the use of statistical techniques to select neural network topology and he concluded that predictions of several steps ahead will suffer from multiplicatively expanding errors. He said further that no statistical technique can extract information where there is none to be found. However, in the general context of classical statistics, there are two major schools of thought regarding the problem of neural network topology selection. According to Hoptroff, (1993), the first one is "to select the simplest class of models which is not inconsistent with the data." This is known as the discerning approach. From a number of different classes select the one that matches the general features evident in the data. The parameters are estimated under the assumption that the particular class of models contains a member that conforms with the underlying mechanism which generated the data. Weigend and Gershenfeld, (1993) claim that this approach was particularly successful until derided in a rigorous study conducted by Swinger, (1996). The irrelevant unit hypothesis (White, 1989b), is the direct equivalent of this approach in the context of neural model selection. Since this approach would lead to a shrink network it was not even considered in its context.

The second and most commonly used statistical approach for topology selection is the so-called discriminating approach (Rumelhart et. al., 1986). It was argued vehemently in this study that the discriminating approach does not make the assumption that a particular class of models contains the operating model. A fitness criterion that measures in some way the lack of fit must be specified. Then the class of models which optimises the fitness criterion is selected. Refenes et. al., (1993) abdicated from this simple procedure and were severely criticised by Swinger, (1996) for making loud claims to the commercial world before they are ready to do so. The main difficulty with the discriminating procedure for neural model selection is that the estimates of the criterion can be relatively imprecise, because the estimation process depends on the unknown underlying function (Rumelhart et. al., 1986). It has to be said of course.

Apart from the aforementioned statistical methods, there is a large number of proposals, which use a variety of fitness criteria and they can be classified in two broad categories: regularisation algorithms (e.g. weight decay) and topology modifying (pruning and constructive) algorithms. Although these algorithms attempt to strike a compromise between model complexity and generalisation ability, they provide arguable comparison with the use of domain expert knowledge on one hand and on the other, variable selection. In doing so they perform parameter estimation and specification testing concurrently. Constructive algorithms start from very simple models and gradually increase the model complexity; using a wide variety of heuristic procedures, until some fitness criterion is satisfied; usually when the learning error starts increasing. Destructive algorithms employ the opposite procedure. The algorithm in this category starts with quite complex neural networks and they gradually move towards more simple topologies. Although it could be argued that regularisation and topology modifying algorithms produce solutions that are biased in principle, in general, they can be viewed as optimisation problems under certain constraints (Swinger, 1996; Bishop, 1995; Allen and Taylor, 1984; Hoptroff, 1993; Weigend and Srivastava, 1995). These constraints are the various control parameters and the quantity optimised being the fitness criterion. The control parameters decide the amount of bias introduced into the selection process and what can be done about them. However, these constraints can be potentially in conflict with other domains.

An important contribution of this paper is to focus the attention of neural network researchers on the need to continue to search for the appropriate network architecture that will take into account the underlying properties of accounting statements and the changing environments in which most companies operate. The organisation of this paper is as follows; Section 4 provide an overview of design related considerations; Section 5 presents two topologies. Section 6 provides application development considerations; Section 7 compares the results from two different topologies. Concluding remarks are presented in section 8.

## 4 DESIGN RELATED CONSIDERATIONS

Many of the rules which govern corporate failure prediction are qualitative or fuzzy, requiring judgement, and hence by definition are not susceptible to purely quantitative analysis. When constructing neural networks, five performance metrics (Refenes and Azema-Barac, 1994) are usually taken into consideration during the design process. However, the mechanisms for controlling these performance metrics (e.g. such as choice of activation function, cost function, network architecture, control terms, learning times) will also be identified.

## 4.1 Network Performance Measures

Convergence concerns the problems of whether the paradigm chosen is capable of learning the classification defined in dataset and under what conditions it does so, and what are the computational requirements for convergence (Nasir et. al., 2000). Simple, straightforward architectures with small samples prove convergence by showing that in the limit, as training time tends to continue, the gradient descent method will tend to zero. However, complex architectures, such as optimal sub-networks prove convergence by showing that in the limit, as training time increases, the gradient descent method will tend to move away from zero. The controlling circumstance in this situation will be to increase the number of training iterations (Nasir et. al., 1999). The main concern in the design of backpropagation networks for nontrivial applications is that it performs learning by steepest descent in weight space, and may be trapped in local minima (Refenes, 1993).

Generalisation measures the ability of a neural network to recognise patterns outside the training set (Refenes et. al., 1994). When designing neural networks, the ability of the network to generalise very well from unseen data is critical to the whole application development. Nasir et al., 2000 suggest that the most important feature of a learning machine is its ability to generalise over the task domain. Refenes et. al., (1993), Taylor and Lisboa, 1997, Nasir et al., 1997; 2000, argued that good generalisation performance on real-world problems is difficult to achieve unless some a priori knowledge about the task domain is built into the system.

Scalability concerns both convergence and generalisation. By scaling up a network, convergence is affected because it takes linear time to perform a single learning iteration through the dataset, however, the number of iterations required increases non-linearly with network size (Refenes et. al., 1993). The reason for this is twofold. First, when extra connections are added to the network, the network size increases and consequentially more weights are added. The dimension space will thus require more training iterations and the added problems of pruning the network if the network get stuck in local minima (Nasir et. al., 1997). Second, the complexities of the search space will bring added complications. For example, the extra connection may require a different transfer and learning function separate from the original connection. It may also require that the extra connection will have to be connected to every other hidden layer in the network before generalisation can be achieved (Nasir et. al., 2000; Refenes et. al., 1993; Taylor and Lisboa, 1997). Scalability of the network would remain an important decision consideration when designing neural networks.

Stability concerns the consistency of the results produced by neural networks when varying the values of the parameters that influence their performance (Refenes and Azema-Barac, 1994). The design consideration concern here is that the data sets used to train the networks should be processed carefully so that when varying parameter values, the results of the network will not change significantly. However, neural networks, like most non-linear systems, have been known to produce wide variations in their predictive properties (Refenes, 1993). The other concern here is that small changes in the network design, learning rules, transfer functions and number of training times may produce large changes in the network behaviour (Taylor and Lisboa, 1997). Refenes (1993) suggest that it is often desirable to identify intervals of values for these parameters that give statistically stable results across different training and test sets. The concern with this suggestion is that financial data do not follow known regularities because of the temporal nature of financial data (Nasir, 1996, Nasir et. al., 1997). What needs to be established in this regard is the intrinsic values if the data rather than the identification of the intervals of values. It is important that the intrinsic values of the parameters are identified purely on the basis of domain knowledge (Nasir, 1996) and also to demonstrate that these identified parameters values persist across different data sets (Brown, 1963).

Sensitivity is the ultimate performance metric for any model of financial application (Refenes, 1993). Its usefulness as a quantitative decision-making tool in financial decision making is enormous. The main goal of a financial analyst is to use the eventual model to simulate 'what if' scenarios, and the ability to have formal framework for reasoning about the model's multivariate prediction ability. It is possible to use a trained financial model of artificial neural network to conduct adequate sensitivity analysis without recourse to statistical approaches. The practical benefit of using a trained neural network to do this is huge. What needs to be done to do this is to select four control mechanisms (e.g. such as the activation function, cost the function, learning rules, and transfer function) to help in conducting a detailed sensitivity analysis of the entire dimensions of the input space. Control mechanisms are rigorously difficult to be determined especially where temporal tendencies exist in financial data of companies. However, once they are correctly determined, as shown in Brown (1963); Nasir et. al.,1997), effective application of neural network can be rather straight forward indeed. Each control mechanism will be edited to reveal detail insight into the network performance so that when evaluating the 'what if' scenarios parameter values can be adjusted accordingly.

Convergence, generalisation, scalability, sensitivity and neural network design would remain the most important experimentation tasks of neural network simulation (Refenes et. al., 1993). It is suggested that generalisation is the main property of design consideration since it determines the amount of data needed to train the network. The conditions which generalisation performance can be obtained are not fully understood by various researchers and this is partly shown in the study conducted by (Refenes et. al., 1993; 1994). The authors provided a common sense rule of minimising the number of free parameters in the network but without reducing the actual size of the network. Whilst this suggestion is acceptable, the main concern is manifestly twofold. First, this suggestion will require long training times and fine-tuning of control parameters during training. This may lead to unexpected local minima especially where control parameters are not identified and selected properly. This approach will be tedious and time consuming. The other concern is that data type may be an impediment to the whole process and may make the entire effort worthless especially when a large-scale complex problem is planned.

## 5 TOPOLOGIES

There are numerous neural network topologies that have been mentioned in literature; however, in this study only two topologies will be considered. The first topology (see Fig. 1) is a fully connected neural network with 174 input variables submitted to it for training. In this topology, domain expert knowledge is not used in organising the data in the network. The second topology (see Fig.2) has the same input variables; however, domain knowledge was used in selecting the topology. Financial expert knowledge of the author was used in organising the data in the network. This is the basis against which to compare results from both topologies.

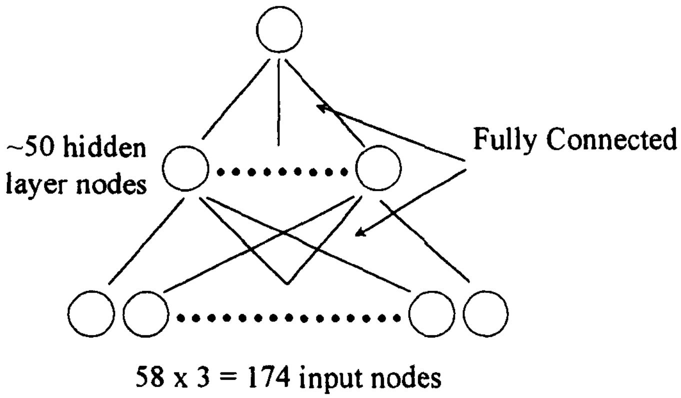


Figure 1: Fully Connected Network (No Domain Knowledge)

The above topology is the multilayered feedforward neural network. It is the most popularly used neural network architecture for single point prediction (Taylor and Lisboa, 1997). The architecture has 174 input nodes with one hidden layer. For each connected network nodes, the output of the network can be compared with the desired output and the error calculated. The weights are then adjusted in proportion to the error and in proportion to their contribution to the activation of each node in order to reduce the error. The errors are then backpropagated and fresh weight calculated as shown in Figure 2 below:

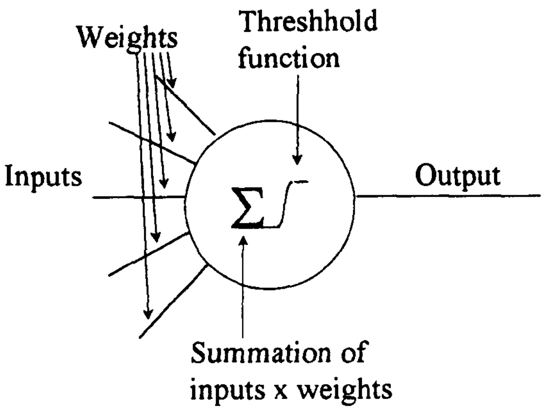


Figure: 2 Adding weights to the model of a neuron

Briefly, in training the network, the following procedures are generally followed. If the input data had been squashed, the data is loaded otherwise input must be normalised. At this point, the network weights are randomised before training can start. The input vector should be presented to the network and the output vector calculated. The next stage is to calculate the error, which is automatically done by the internal mechanisms of the network. The weights of the network are then adjusted for fine-tuning and the network tested for prediction capability.

**TOPOLOGY 2**

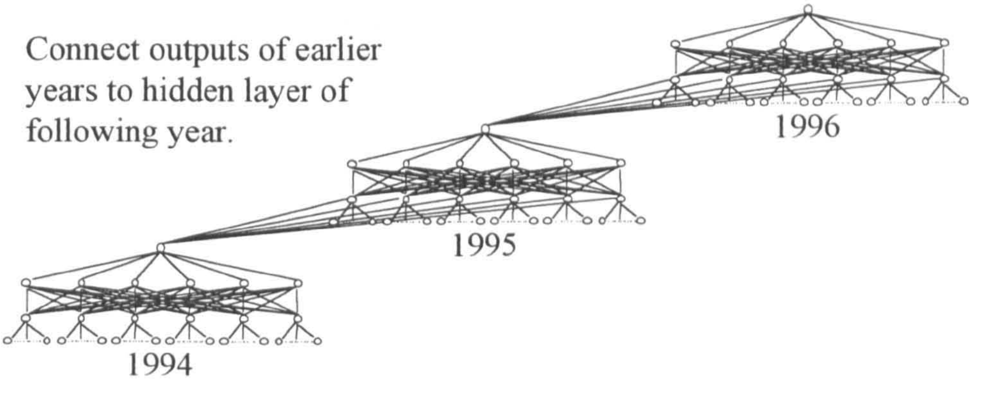


Figure 3: Building in Time Neural Network Architecture (Inter-Connected)

The architecture above is a multilayered feedforward neural network with the backpropagation algorithm. The architecture has 58 input variables for each year (58 x 3) plus 4 economic and political factors inputs, thus making 178 input units overall.

## 6 APPLICATION DEVELOPMENT CONSIDERATIONS

Developing a successful neural network application involves several stages. The initial stage is collection of data where domain knowledge can be used to select appropriate financial indicators of failure. The effectiveness of neural networks can be affected by spurious data; the solution lies in the research and criteria behind data sources and selection (David et. al., 1997; Duffy, 1997; Nasir, 1996.) The stages are narrated succinctly below:

### 3.1 Sample Determination

Data Sources:

a) The London Stock Exchange
b) Jordans Financial Database
c) The Bank of England
d) The Institute of Directors

Total Sample Size: 270,000 major public and private British companies

Reduction Process:

a) Exclude new firms
b) Exclude small firms
c) Exclude firms by Turnover
d) Exclude firms with small assets
e) Exclude overseas subsidiaries

Selection Criteria:

a) Define period of study
b) Define Bankrupt company
c) Define Non-Bankrupt company
d) Define "mates" category
e) Final selection: 2500 companies

Select Input Variables for:

| | | | | |
|---|---|---|---|---|
| Balance Sheet Network | (10) | 1994 | 1995 | 1996 |
| Profit & Loss Network | (8) | 1994 | 1995 | 1996 |
| Cash Flow Network | (10) | 1994 | 1995 | 1996 |
| Financial Summary | (6) | 1994 | 1995 | 1996 |
| Key Financial Ratios | (20) | 1994 | 1995 | 1996 |

## 7 RESULTS: TRAINED NEURAL NETWORK MODELS

The software used for this work is NeuralWare Professional Development Plus/2 System (NeuralWare© NeuralWorks™ 2/Plus v5.30, 1996). The overall environment forms an efficient and easily expandable tool for methodological development. The tool allows selection from any of the major network types to create any of the 28 major paradigms and dozens of variations well supported by the product.

Two topologies are trained for comparison. The first (Topology 1) is the fully connected neural network will all the possible input variables submitted to it without the use of domain of domain knowledge in network construction and data organisation in the network. The second is the preferred model. Topology 2 is made of a series of inter-connected networks each connected to its immediate neighbours. Thus the hidden layer in 1995 receive additional input from the 1994 network and the hidden of 1996 receive additional input from the 1995 network and provide an encoding of a three year period. There is a feedforward connection between the input units to the first hidden layer and full connection between the two hidden layers. High level topology captures temporal nature of data. Low level (i.e. connection between input units to the first hidden layer) topology of sub-networks uses domain knowledge. Figure 3 shows the chosen structure.

Topology 1 was trained with eighteen hidden units. Using standard error, we chose Hyperbolic Tangent (TanH) as the transfer function. The network learning was the learning Delta Rule. A total number of 20 runs were conducted and the results of the best run (Run 16) are presented in this paper. The global learning schedule is shown Table 1 below:

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 150000 | 85000 | 200000 | 10000 | 280000 |
| Momentum | 0.20 | 0.10 | 0.20 | 0.30 | 0.40 |
| Error Tolerance | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| Noise Decay | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Learning Rate | 0.10 | 0.20 | 0.10 | 0.10 | 0.20 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| GAIN | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |

Table: 1: Global Learning Schedule

The data was in three sets - 1400 companies in the training set, 400 companies in the test, and 700 companies in the validation set. The test set is then used to evaluate network performance. Validation set (unseen) is merely used to validate the network. Using the measurements of 58 input variables of 2500 companies, a backpropagation network (fully connected) is shown in Figure 1. The training of this network was stopped after 250,000 iterations.

## 6 RESULTS (Topology 1)

The results generated represent training cases for 2500 companies. The input measurements used were 58, representing the Cash Flow network, Profit and Loss Statement network, Balance Sheet Network, Key Financial Ratios Network, Financial Summary Network, and Economic and Political factors Network. When evaluating the predictive capability of the neural network, a testing threshold, similar to the training tolerance, is specified. This testing threshold identifies how stringent the allowable variation in output neurons can be when predicting the status of the companies in the training set. In this study, four testing threshold were used; 0.50 and 0.50, 0.20 and 0.80, 0.10 and 0.90 and 0.05 and 0.95. This basis was used for correct and incorrect classifications for the neural network model. When checking the neuron output for both criteria, the network achieved the following results:

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 44 | % healthy wrong | 56 | % healthy don't know | 0 |
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 59 | % bankrupt wrong | 1 | % bankrupt don't know | 40 |
| % Healthy right | 12 | % healthy wrong | 14 | % healthy don't know | 73 |
| Classification Criteria | 0.1 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 30 | % bankrupt wrong | 1 | % bankrupt don't know | 68 |
| % Healthy right | 06 | % healthy wrong | 13 | % healthy don't know | 81 |
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 15 | % bankrupt wrong | 1 | % bankrupt don't know | 68 |
| % Healthy right | 14 | % healthy wrong | 12 | % healthy don't know | 83 |

Table 2: Neural Network Results (Topology 1)

As revealed in Table 2 above, there were 72 bankrupt companies and 328 healthy companies. Using the 0.1 and 0.90 criteria, the network correctly classified 30% of bankrupt companies and returning 68% as don't knows. The network misclassified 1% of bankrupt companies. Looking at the healthy companies, the network correctly classified 6% of healthy companies and returning 81% as don't knows. The network misclassified 13% of bankrupt companies. Using a more stringent criteria; 0.05 and 0.95, the network correctly classified 15% of bankrupt companies and returning 68% as don't knows. The network misclassified 1% of bankrupt companies. The network correctly classified 14% of healthy companies and returning 83% as don't knows. The network misclassified 12% of healthy companies.

Topology 2: Results

The results obtained from topology 2 as shown in Figure 2 are now presented.

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 96 | % healthy wrong | 4 | % healthy don't know | 0 |
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 94 | % bankrupt wrong | 3 | % bankrupt don't know | 3 |
| % Healthy right | 96 | % healthy wrong | 3 | % healthy don't know | 1 |
| Classification Criteria | 0.1 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 90 | % bankrupt wrong | 3 | % bankrupt don't know | 7 |
| % Healthy right | 95 | % healthy wrong | 2 | % healthy don't know | 4 |
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 10 |

Table 3: Neural Network Results (Topology 2)

As revealed in Table 3 above, there were 72 bankrupt companies and 328 healthy companies. Using the 0.1 and 0.90 criteria, the network correctly classified 90% of bankrupt companies and returning 7% as don't knows. The network misclassified 3% of bankrupt companies. Looking at the healthy companies, the network correctly classified 95% of healthy companies and returning 4% as don't knows. The network misclassified 2% of healthy companies. Using a more stringent criteria; 0.05 and 0.95, the network correctly classified 85% of bankrupt companies and returning 13% as don't knows. The network misclassified 3% of bankrupt companies. The network correctly classified 89% of healthy companies and returning 10% as don't knows. The network misclassified 1% of healthy companies. These results were obtained after 65 network runs. The reason for this is that at every run, there were improving scope for better results. Unlike with the fully connected network where there were no improvements in results between runs and as mentioned earlier, training iterations stopped after 20 runs.

## 8 CONCLUDING REMARKS

This paper has addressed two important issues. The first had been a method for determining the topology of feedforward neural networks. Although the general taxonomy had been presented very briefly due to lack of space. The technique used is based upon the fact that the number of neurons for each layer is related to the complexity of the input data and upon the properties of the nonlinear mapping from input to output. In essence, the number of hidden neuron for each layer is chosen by analysis of the data organisation in the network in respect to the dimensions of the input and output subspaces. The use of domain knowledge to determine the general taxonomy help to avoid the problems associated with over or under-specification of the number of hidden nodes. Moreover, the procedure provides a practical approach for arriving at the unique best approximation for the topology selected. This has been illustrated by the experiments conducted for both topologies.

The second issue had been the comparison of two topologies for evaluation purposes. It has been shown in this paper that conventional neuro-forecasting methods of point predictions (see Topology 1) usually predict the next time step, which is insufficient where temporal tendencies exist in the financial data. We have therefore suggested a method for training a neural network to predict the entire conditional probability density. The application of our method to Topology 2, for which conventional method of point predictions is insufficient or completely inappropriate has achieved very satisfying results (see Table 3). However, so far the method has not been applied to real world time series. We have therefore provided a novel approach for dealing with temporal tendencies in financial data.

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# Predicting Corporate Bankruptcy using Inter-Connected Artificial Neural Networks

M.L. Nasir, R.I. John, S.C. Bennett
Centre for Computational Intelligence
De Montfort University
The Gateway, Leicester LE1 9BH, United Kingdom
Phone: +44 (0) 1162 551 551, Fax: +44 (0) 1162 541 891
email: mln@dmu.ac.uk

ABSTRACT: The aim of this study is to show that domain knowledge and time dependent structured artificial neural networks can successfully discern patterns or trends in financial data and use them as early warning signals of distressful conditions in current viable firms. It was shown that with careful neural network design, the backpropagation learning procedure is an effective way of training neural networks where temporal tendencies exist. Missing values, hidden data, financial outliers can pose problems in determining which variables best capture the process at hand. In this paper, we discuss how to identify these problems and reduce the problem space. A large amounts of historical financial data was obtained from The London Stock Exchange. Economic and Political data was obtained from the Bank of England and Institute of Directors.

KEYWORDS: Neural Networks, Inter-connected neural networks, Learning, Data Analysis, Modelling, Domain Knowledge, Missing Values, Financial Outliers, and Hidden Data.

## 1 INTRODUCTION

A vast amount of literature has emerged concerning the development of the appropriate neural network architecture for predicting corporate bankruptcies. The current tendency in failure prediction emphasises the use of simple models derived from the financial data one year prior to failure. It would remain a matter of grave concern that in corporate failure prediction research, most attention have been paid to static problems, i.e. deriving models from one year prior to failure data of failed companies, for which conventional feedforward backpropagation networks are adequate, there exist alternative architectures for handling time-varying problems in financial modelling. This study proposes a new approach for implementing inter-connected neural networks for handling temporal tendencies.

An important contribution of this paper is to focus the attention of neural network researchers on the need to continue to search for the appropriate network architecture that will take into account the underlying properties of accounting statements and the changing environments in which most companies operate. The organisation of this paper is structured as follows. In section 2, we present an overview of relevant research in a nutshell. Section 3 explains application development considerations. We discussed, very briefly, missing values, missing data and hidden data in section 4. We present our application in section 5. Finally, we present the results of our study in section 6.

## 2 BRIEF REVIEW OF RELEVANT RESEARCH

Corporate failure defies precise definition (Altman, 1968; 1993, Altman et. al., 1976). Financial failure occurs when the enterprise has chronic and serious losses or when the company becomes insolvent with liabilities disproportionate to the assets. The generally accepted reasons for corporate bankruptcy are poor management, autocratic leadership, failure to operate successfully in the market place, or inability to pay debts when due (Altman, 1993; Alici and Valtchanov, 1994, Beaver, 1977). These factors have all been implicated in the collapse of many companies.

Beaver (1977) was among the first to use financial ratios to predict corporate bankruptcy. Using a paired sample analysis, with size and industry type used as basis for pairing, he found overwhelming evidence of differences in the ratios of failed and healthy companies. To test the predictive power of ratios, he used a dichotomous classification technique, and found the cash flow to total debt ratio to be the best predictor of failure. Beaver thought that liquidity ratio alone can predict corporate failure that will occur in five years time. The limited success of this basic approach (although a great deal of effort was devoted to it) could be attributed to several factors. In summary, two main reasons are identified. First, the basic methodology enables only a single determinant (univariate) from a large set of financial ratios to be analysed concurrently. But many factors are always implicated in the failure of the company. In addition to this point, classical techniques for decision making and prediction do not work well for many applications with restricted sample sizes and non-linearities in the data set. A univariate technique of forecasting is only capable of picking out trends, and will have considerable difficulty in modelling cycles that are by no means repetitive in amplitude, period or shape. Second, and possibly even more important, the structural relationship between predicting corporate failure and its causes changes over time. These changes can be abrupt and catastrophic. The failure of Barings Investment Bank in the UK is a damning example. This phenomenon of unstable structural parameters (financial variables) in corporate failure modelling is a special case of a general fundamental critique of univariate method of analysis (Aziz and Lawson, 1988; Beaver, 1977; Casey and Bartczak, 1984).

Altman (1993), improved on Beaver's univariate method of analysis by introducing the multivariate approach, which allows for the simultaneous consideration of five variables in the prediction of corporate failure. The approach is that of the multivariate discriminant analysis (MDA). Discriminant analysis is a statistical technique used to construct classification schemes so as to assign previous unclassified observations to the appropriate group. Altman based his work on groups of appropriate financial reports extracted from company accounting statements. His work (known as Altman's Z-Scores) was expressed as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.0033X_3 + 0.006X_4 + 0.999X_5$$

In which Z = the overall solvency index and $X_1$ to $X_5$ are the independent variables.

$X_1$ = working capital to total assets
$X_2$ = retained earnings to total assets
$X_3$ = earnings before interest and taxes to total assets
$X_4$ = market value of equity to book value of total assets
$X_5$ = sales to total assets

Altman used a MDA programme to calculate the numeric values as shown above. The Z values were used to classify companies as either bankrupt or non bankrupt. Where the Z-score was below 1.81, the company was considered to be failing; where it was above 2.99 it was considered to be healthy. The multivariate discriminant analysis had its difficulties, and its limited success can be attributed to one main reason. The standard discriminant analysis procedures assume that the variables used to describe members of the groups of companies being investigated are normally distributed (Alici and Valtchanov, 1994; Alici and Gifford, 1995). This assumption may not be valid especially when modelling the predictions of corporate failure where deviations from the normality assumption appear to be the rule rather than the exception. This implies, that violations of the normality assumptions may bias the test of significance and estimated error rates (Betts and Belhoul, 1987; Altman et.al., 1994; Argenti, 1976). There are other remaining problems that have either not been mentioned or only briefly touched upon.

A broad alternative approach is one based on artificial neural networks (ANN). The use of these quasi-biological structures should not of course be seen as an anodyne in itself. Neural networks suffers from the inability to explain their own predictions. While this is a damning consequences of using artificial neural networks, they represent the best way forward in predicting corporate failure especially where temporal tendencies exist.

## 3 APPLICATION DEVELOPMENT CONSIDERATIONS

Developing a successful neural network application involves several stages. The value of having a fundamental understanding of the problem domain cannot be over stated. It is this understanding of the underlying process that gives us material to draw from when developing our strategies and experimenting with relationships within data. The effectiveness of neural networks can be affected by spurious data; the solution lies in the research and criteria behind data sources and selection (David et.al., 1997; Duffy, 1997). Because of lack of space, the stages are narrated succinctly below:

### 3.1 Sample Determination

| | | |
|---|---|---|
| Data Sources: | a) | The London Stock Exchange |
| | b) | Jordans Financial Database |
| | c) | The Bank of England |
| | d) | The Institute of Directors |

Total Sample Size: 270,000 major public and private British companies

Reduction Process:

| | | |
|---|---|---|
| | a) | Exclude new firms |
| | b) | Exclude small firms |
| | c) | Exclude firms by Turnover |
| | d) | Exclude firms with small assets |
| | e) | Exclude overseas subsidiaries |

| | | |
|---|---|---|
| Selection Criteria: | a) | Define period of study |
| | b) | Define Bankrupt company |
| | c) | Define Non-Bankrupt company |
| | d) | Define "mates" category |
| | e) | Final selection: 2500 companies |

Select Input Variables for:

| | | | | |
|---|---|---|---|---|
| Balance Sheet Network | (10) | 1994 | 1995 | 1996 |
| Profit & Loss Network | (8) | 1994 | 1995 | 1996 |
| Cash Flow Network | (10) | 1994 | 1995 | 1996 |
| Financial Summary | (6) | 1994 | 1995 | 1996 |
| Key Financial Ratios | (20) | 1994 | 1995 | 1996 |

## 4 NON-NORMALITY IN FINANCIAL DATA

Financial data may be viewed as random variables which (imperfectly) reveal information about a company's financial and operating activities. Inferences based on such information from cross-sectional financial data will be dependent upon the characteristics of the underlying non-linearity generating these data and whether these can be identified. Intuitively, when financial statements are processed and analysed, there are always multivariate problems (outliers, missing values, multicollinearity, hidden data, and creative accounting practices) which have to be dealt with accordingly. Multivariate problems in financial data would remain a bottleneck when preparing financial data for neural inputs (Lev and Sunder, 1979; Lipmann, 1984; Lee and Wu, 1988; Nasir et.al., 1998; ).

### 4.1 Handling Missing Values

The use of financial data in a variety of performance evaluations and decision-making contexts is an increasingly important area of accounting research and practice (Deaking, 1976; Lev and Sunder, 1979). Missing values can pose problems in determining which variables best capture the process at hand. The goal was to find the simplest explanation of facts using fewest variables. As a result, it is best to identify all missing values because it can reduce the problem space. Deaking (1976) suggests that an averaging method can be applied to fill in the missing value with the average of the last value and the next valid value. The practical difficulty with this approach is that averaging may be inappropriate because financial parameters are not determined by trend within periods, but by taking into consideration various activities of the firm and pronouncements by the Accounting Standards Board (David et.al., 1997). For example, a company may pay corporation tax for 1994 at £34m and 1996 at £40m but report losses in 1995 and may not suffer any corporation tax on profits for the period. To apply averaging in this case would be misleading. Further, corporation tax payable on profits in one period often bears little or no relationship with the tax payable in another period. The normality assumption is therefore not valid in Deaking's work. Lev and Sunder (1979) suggest that one could use the mean, maximum, or minimum of the entire field. This approach again is fraught with difficulties. Companies operate in accordance with certain policies which vary between accounting periods as agreed by the directors at Board meetings. Having said that, accounting policies are prepared in the interest of the company and therefore vary according to the issues facing the company at a particular point in time. To apply the minimum or maximum of the entire field would be totally misleading.

### 4.2 Handling Financial Outliers

Perhaps the greatest difficulty in pre-processing financial data for neural network inputs is the widespread existence of outliers in financial ratios. Outliers can be regarded as one of the main reasons for the absence of normality in financial ratios.

Deaking (1976) suggests that outliers in financial ratios should be deleted. This approach may give ground for concern. Lack of fit of financial ratio data to multivariate normality is amplified when some observations in financial data are multivariate outliers. In contrast to outliers in univariate analysis, multivariate financial outliers may consist of data values that do not simply spin out at the ends of univariate distributions. Having said that, multivariate data values may also be discordant (conflicting) because of subtle, unexpected patterns of values on subsets of financial variables. Furthermore, multivariate financial outliers have disproportionate influences on parameter estimates and on the predictions of corporate bankruptcy (Lee and Wu, 1988). To delete them will not solve the problem but add more to the problems of multivariate nonnormality in financial data analysis. Knowledge from practice would suggest that the basic characteristics of the outliers should be determined and compared to the entire population in the data set. It may be that there are some irreconcilable factors affecting the two groups. It may also be that the outliers represent a completely different industrial sector, or at worst, the data should not have been there in the first place. The reasons for the existence of the outliers should therefore be examined and reconciled with the entire population. This is important because it is possible that several variables, when examined individually, may be univariate normal and yet their multivariate distribution is nonnormal. If any reconciliation is not possible, then the procedure for sampling and selection of data must be revisited and possibly revised. Regrettably, univariate outlier identification and deletion procedures ensure neither multivariate normality nor equal covariance matrices (Lau, 1987).

### 4.3 Handling Hidden Data.

Hidden data occurs when the directors of a company have decided to withhold confidential information about their firm's strengths and weaknesses. This could be done in order to hide information about their imminent collapse or simply to preserve the interests of the company so as to avoid a take over raid from competitor large firms. A company is legally allowed to do this if to do otherwise would bring about a predator and victim situation and also, to protect the interests of the company. Knowledge from experience in handling this kind of problem is to obtain descriptive information about the company which is contained in the financial statements known as internal sources together with external information deduced from reading economic reports available in the public domain. One source of information is the Financial Times. Once this descriptive information has been obtained, it can be analysed as symbolic data and then one can use a one-of-N-transformation as numeric format for neural inputs. The characteristics of hidden data themselves are multivariate nonnormal which may escape undetected due to the masking effects of other extreme observations. Care should therefore be taken when using these symbolic data or their transformation as numeric input to neural networks.

## 5 TRAINED NEURAL NETWORK MODEL

The software used for this work is NeuralWare Professional Development Plus/2 System (NeuralWare© NeuralWorks™ 2/Plus v5.30, 1996). The overall environment forms an efficient and easily expandable tool for methodological development. The tool allows selection from any of the major network types to create any of the 28 major paradigms and dozens of variations well supported by the product.

This model is made of a series of inter-connected networks each connected to its immediate neighbours. Thus the hidden layer in 1995 receive additional input from the previous 1994 and the hidden of 1996 receive additional input from the previous 1995 and provide an encoding of a three year period. There is a feedforward connection between the input units to the first hidden layer and full connection between the two hidden layers. High level topology captures temporal nature of data. Low level (i.e. connection between input units to the first hidden layer) topology of sub-networks uses domain knowledge.

The network was trained with eighteen hidden units. Using standard error, we chose Hyperbolic Tangent (TanH)as the transfer function. The network learning was the learning Norm-Cum-Delta Rule. The global learning schedule is shown Table 1 below:

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 50000 | 45000 | 60000 | 10000 | 10000 |
| Momentum | 0.20 | 0.10 | 0.20 | 0.30 | 0.40 |
| Error Tolerance | 0.10 | 0.10 | 0.10 | 0.10 | 0.10 |
| Noise Decay | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Learning Rate | 0.10 | 0.20 | 0.10 | 0.10 | 0.20 |

Table: 1: Global Learning Schedule

There were three training sets. There were 1400 companies in the training set, 400 companies in the test, and 700 companies in the validation set. The unseen test set is then used to evaluate network performance. Validation set (unseen) is merely used to validate the network. Using the measurements of 58 input variables of 2500 companies, a backpropagation network (inter-connected) as shown below was successfully trained after 175,000 iterations.


Figure: 3. Structure of the inter-connected neural sub-networks

## 6 RESULTS

The results generated represent training cases for 2500 companies. The input measurements used were 58, representing the Cash Flow network, Profit and Loss Statement network, Balance Sheet Network, Key Financial Ratios Network, Financial Summary Network, and Economic and Political factors Network. When evaluating the predictive capability of the neural network, a testing threshold, similar to the training tolerance, is specified. This testing threshold identifies how stringent the allowable variation in output neurons can be when predicting the status of the companies in the training set. In this study, two testing threshold were used: 0.1 and 0.9 and 0.05 and 0.95. This basis was used for correct and incorrect classifications for the neural network model. When checking the neuron output for both criteria, the network achieved the following results:

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.1 and 0.90 | | | | |
| No of Bankrupt | 71 | | | | |
| No of Healthy | 329 | | | | |
| % Bankrupt right | 82 | % bankrupt wrong | 6 | % bankrupt don't know | 13 |
| % Healthy right | 92 | % healthy wrong | 1 | % healthy don't know | 7 |
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 71 | | | | |
| No of Healthy | 329 | | | | |
| % Bankrupt right | 66 | % bankrupt wrong | 6 | % bankrupt don't know | 28 |
| % Healthy right | 87 | % healthy wrong | 1 | % healthy don't know | 12 |

Table 2: Neural Network Results

## 7 CONCLUDING REMARKS

This paper has shown that neural networks can perform better that the traditional techniques of corporate failure prediction. Empirical results suggest that artificial neural networks can perform better than its classical counterparts where noisy and random environment exists. We have therefore shown that, a wide range of cases can be included in modelling corporate failure and yet obtain better results than has ever been published. Backpropagation networks are notoriously difficult to train where large data set is introduced. We have been able to overcome some of the known difficulties by introducing piecemeal iterations to the network and also, by appropriating training parameters.

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## Appendix B Bankruptcy Table

This section contains list of bankrupt companies (public and private) between 1995 and 1999.

| Period | Companies that ceased to trade |
|---|---|
| 1994 | 708 |
| 1995 | 843 |
| 1996 | 1489 |
| 1997 | 2129 |
| 1998 | 2625 |
| 1999 | 2814 |

Source: JORDANS Financial Database of major British Public and Private Companies.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1994* | 8,534 | 8,534 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 708 |

**Total number of companies selected** 708

Clear Search | Show Boolean | Save Strategy | Save Co. Set

ⓘ **You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1995* | 11,083 | 11,083 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 843 |

**Total number of companies selected** 843

Clear Search | Show Boolean | Save Strategy | Save Co. Set

**You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1996* | 18,700 | 18,700 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 1,489 |

**Total number of companies selected** 1,489

Clear Search | Show Boolean | Save Strategy | Save Co. Set

**You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1996* | 18,700 | 18,700 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 1,489 |

**Total number of companies selected** 1,489

Clear Search | Show Boolean | Save Strategy | Save Co. Set

ⓘ **You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✓ | 1. *Latest Year* | *1997* | 39,727 | 39,727 |
| ☒ | ✎ | ✓ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 2,129 |

**Total number of companies selected** 2,129

Clear Search | Show Boolean | Save Strategy | Save Co. Set

ⓘ **You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✓ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1998* | 284,886 | 284,886 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 16,201 |

**Total number of companies selected** 16,201

Clear Search | Show Boolean | Save Strategy | Save Co. Set

**You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Search Summary

| Delete | Edit | Enable | Criteria | Selected | Step Result | Search Result |
|---|---|---|---|---|---|---|
| ☒ | ✎ | ✔ | 1. *Latest Year* | *1999* | 63,290 | 63,290 |
| ☒ | ✎ | ✔ | 2. *Types of Non Trading Companies* | *Companies that ceased to trade* | 26,625 | 2,814 |

**Total number of companies selected** 2,814

Clear Search | Show Boolean | Save Strategy | Save Co. Set

**You can change your search by:**

- ☒ Permanently deleting a search step
- ✎ Editing a search step
- ✔ Temporarily including or removing a search step so you can see what affect this has on your search

To do this click on the relevant option for your chosen step. If you select edit it will take you back to the relevant search screen. If you select delete the corresponding step will be deleted.

If you want to view the companies then click on list or report at the top of the screen.

## Appendix C – Companies used as part of training sets

As part of the modelling process, 2,500 companies were selected randomly from a defined population of companies. The following listing provides the full names of companies (bankrupts and non-bankrupts) used as part of training sets. Recall that 'independent variables' were also selected, however, the lists are as shown in Table 4.1.

| COMPANY NAME | Registered Number | SIC Code |
|---|---|---|
| WASTE MANAGEMENT INTERNATIONAL PLC | 02669336 | 5157 |
| DORSUB (DPR) LIMITED | 01002994 | 5242 |
| DORSUB (TS/TM) LIMITED | 00461668 | 5242 |
| DORSUB (HRL) LIMITED | 00243154 | 5242 |
| SGS REALISATIONS LTD | 00177877 | 7310 |
| DORSUB (PRL) LIMITED | 00397489 | 5242 |
| TAMARIS PLC | 01698076 | 8514 |
| BARFORCE LIMITED | 00310708 | 5242 |
| CUK (MVL) LIMITED | 00368976 | 1533 |
| MOSTCASH PLC | 02010490 | 2121 |
| ADVANTAGE GROUP LIMITED | 00834285 | 8514 |
| HOLLAS GROUP PUBLIC LIMITED COMPANY(THE) | 00494615 | 1771 |
| MOORFIELD HOLDINGS LIMITED | 02502281 | 3614 |
| TAWNEYDOWN PLC | 02275768 | 6523 |
| JDG DRAKE PLC | 01523083 | 4521 |
| CARE ALTERNATIVES LIMITED | 01998074 | 8532 |
| STAG GROUP LIMITED | 00136403 | 3614 |
| ABI LEISURE GROUP PLC | 02258157 | 3420 |
| DAWN TIL DUSK HOLDINGS PLC | 03271694 | 7499 |
| FUJITSU MICROELECTRONICS LIMITED | 01709971 | 3120 |
| CHASLEY (LIFESTYLE) PLC | 01955986 | 9261 |
| B. UPHOLSTERY (REALISATIONS) LIMITED | 02526132 | 3611 |
| POL REALISATIONS LIMITED | 00451157 | 7484 |
| ARCADIA HEALTHCARE PLC | 01470645 | 9305 |
| TEMPS SELECT LIMITED | 02631780 | 7450 |
| JOH HOLDINGS LIMITED | 01290361 | 3614 |
| MIDDLETON MAINTENANCE GROUP PLC | 00875637 | 9305 |
| TEXTILION LIMITED | 02320230 | 1760 |
| M. & N. PLANT LIMITED | 01522057 | 4521 |
| NATIONAL HOMECARE GROUP LIMITED | 03046263 | 7414 |
| LGS RECONSTRUCTION LIMITED | 02159151 | 2754 |
| PDC CONSTRUCTION LIMITED | 01168955 | 4521 |
| CADORO PLC | 00057837 | 5243 |
| DAWN TIL DUSK PLC | 02014276 | 5212 |
| CHRISTIES PANEL PRODUCTS LIMITED | 01569675 | 3614 |
| DELANEY GROUP P.L.C. | 00824525 | 3611 |
| TREES PARK VILLAGE LIMITED | 02477455 | 9305 |
| TECHNIC GROUP PLC | 02144393 | 2513 |
| CALCOT HOTELS LIMITED | 00704935 | 5511 |
| MILBANK FOODS LIMITED | 00841460 | 5212 |
| SMALLSHAW GROUP LIMITED | 02524184 | 1771 |
| ACAR (REALISATIONS) LIMITED | 00873950 | 1751 |
| EDGEMOND GROUP LIMITED | 02704827 | 2875 |
| G.A.WOODCOCK.LIMITED | 00106974 | 6340 |
| CH (INTERNATIONAL REALISATIONS) LIMITED | 01984993 | 3110 |
| THE HARLAND GROUP LIMITED | 00123765 | 2924 |
| PEVENSEY BAY LIMITED | 00555916 | 9301 |
| MACKIE INTERNATIONAL GROUP PLC | 02956689 | 2954 |
| HADLEIGH PLC | 01299631 | 3550 |
| THE J. BLAKE GROUP LIMITED | 02384714 | 5010 |
| KC (REALISATIONS) LIMITED | 01501650 | 2524 |
| KWH (REALISATIONS) LIMITED | 02682740 | 2524 |
| FENWORTH LIMITED | 00749717 | 2710 |
| OTRA UK LIMITED | 02594149 | 5143 |
| M & N CONTRACTORS LIMITED | 01956753 | 4525 |
| J.BLAKE & CO. LIMITED | 00181020 | 5010 |
| ARROWVALE LIMITED | 01775683 | 1717 |
| NH REALISATIONS LIMITED | 01862253 | 5272 |
| ANCASTER INVESTMENTS LIMITED | 02042174 | 7220 |
| WOODSIDE HEALTH CARE LIMITED | 01888933 | 9305 |
| ONWA ELECTRONICS (U.K.) LIMITED | 02656948 | 2971 |
| THE HCG GROUP LIMITED | 03073424 | 2875 |
| MILL HILL KNITWEAR LIMITED | 01169603 | 1771 |
| STRACHAN HENSHAW MACHINERY LIMITED | 02456298 | 2924 |
| O'HARE LIMITED | 01181818 | 4531 |
| THE OFFICECARE GROUP LIMITED | 02517874 | 9305 |
| WOODCOCK TRAVEL LIMITED | 00943205 | 6330 |
| GOSTORM LIMITED | 02985645 | 7499 |
| HARLEQUIN GROUP PLC | 02002807 | 3002 |
| LIQUICK 211 LIMITED | 00597546 | 2744 |
| CHS ELECTRONICS PLC | 01070796 | 3002 |

| | | |
|---|---|---|
| CHAMBERLAIN PHIPPS MATERIALS LIMITED | 03265513 | 2513 |
| OTRA B LIMITED | 00132783 | 5143 |
| PDL REALISATIONS LIMITED | 02862812 | 2753 |
| COUNTAREA LIMITED | 02997747 | 2861 |
| CORNER COVENTRY LIMITED | 02300642 | 5010 |
| WER (MVL) (1998) LIMITED | 01161666 | 3140 |
| WHITWORTH'S FOODS GROUP LTD | 02686571 | 1533 |
| QUEENBOROUGH ROLLING MILL CO. LIMITED | 01067887 | 2710 |
| FOUR SEASONS OF LONDON PLC | 00991441 | 5142 |
| KNOCKIN LIMITED | 02358877 | 4521 |
| COTON EXECUTIVE SERVICES LIMITED | 01848681 | 7450 |
| UNIVERSAL BULK HANDLING LIMITED | 02520448 | 2875 |
| WHYTE KNIGHTS LIMITED | 02788535 | 5010 |
| JOHN CLELAND GROUP LIMITED | 03125381 | 2222 |
| DUDLEY DROP FORGING,COMPANY LIMITED | 00191353 | 2840 |
| PROPERTY PARTNERSHIPS PUBLIC LIMITED COMPANY | 00728442 | 7011 |
| FULL CIRCLE INDUSTRIES PLC | 02650119 | 2523 |
| R.E.INGHAM & COMPANY LIMITED | 00580327 | 3230 |
| EWB 1999 LIMITED | 00294709 | 4521 |
| ARCON GROUP LIMITED | 01071472 | 5144 |
| EMPRESS CAR CO.(ABERTILLERY) LIMITED | 01018120 | 5010 |
| FREDERICK COOPER ARCHITECTURAL DISTRIBUTION LIMITED | 02524082 | 5144 |
| HOULT SECURITY SERVICES LIMITED | 01775364 | 9305 |
| LW REALISATIONS 1998 LIMITED | 00556374 | 2722 |
| CANNOCK GROUP LIMITED | 03097513 | 3650 |
| CARE SECURITY SERVICES LIMITED | 01707808 | 7460 |
| HERRBURGER BROOKS PLC | 00166947 | 3630 |
| G.S.I. TRAVEL AND TRANSPORTATION (U.K.) LIMITED | 02367138 | 7220 |
| WAHLCO ENGINEERED PRODUCTS GROUP LIMITED | 02625927 | 2875 |
| NINKAPLAST (U.K.) LIMITED | 02250641 | 2524 |
| CROWCASTLE LIMITED | 01331649 | 5261 |
| JAMES SHIRES & SONS LIMITED | 00576665 | 1722 |
| RAVANE TWO LIMITED | 02434004 | 7110 |
| MANOR HOUSE HOSPITAL LIMITED | 03132020 | 8511 |
| CAM DESIGNS LIMITED | 01923016 | 7420 |
| PROPERTY PARTNERSHIPS (HOTELS) LIMITED | 01191593 | 5511 |
| PLANE TRUCKING LIMITED | 01537155 | 6024 |
| WOODLAND POTTERIES LIMITED | 02560872 | 2625 |
| KONTRON INSTRUMENTS LIMITED | 01080337 | 3320 |
| METROLOGIE LIMITED | 01195678 | 5164 |
| NEW SOUTH MILLS LIMITED | SC154367 | 1712 |
| ZEETACO LIMITED | 01881037 | 7484 |
| M.G.A. DEVELOPMENTS LIMITED | 01402915 | 2852 |
| ROBINS CINEMAS LIMITED | 02414004 | 9212 |
| CYBERDESK COMPUTER SERVICES LIMITED | 01901569 | 7220 |
| RESOURCE & TECHNOLOGY MANAGEMENT LTD | 02654378 | 7220 |
| A.S.G.HOLDINGS LIMITED | 00765598 | 7011 |
| A.S.G.-SWIFTS LIMITED | 00840093 | 3663 |
| CLUMBER HOMES LIMITED | 01712037 | 9305 |
| B. & D. (PUBLIC WORKS) CONTRACTORS LTD | 03030675 | 4521 |
| TOGAMOOR LIMITED | 01944319 | 1722 |
| HLQ REALISATIONS LIMITED | 02752574 | 7220 |
| FIRST OLYMPIAN SECURITIES LIMITED | 00453124 | 3130 |
| NCT CAR TRANSPORTERS LIMITED | 01436259 | 6024 |
| TRAVELBASE LIMITED | 02732189 | 6330 |
| THE CAR GROUP PLC | 03100751 | 5010 |
| THE SCOTTISH COLLEGE OF TEXTILES | SC012414 | 8030 |
| W.W. JOHNSON & SON LIMITED | 01491251 | 5170 |
| HEATHCOTE & IVORY LIMITED | 01831177 | 3663 |
| R STEWART GROUP LIMITED | 02829730 | 4521 |
| CLARKE & SMITH INDUSTRIES LIMITED | 00711916 | 2754 |
| SPARTAN REDHEUGH LIMITED | 00596005 | 2710 |
| EXPLORATION HOLDINGS LIMITED | 02812999 | 7414 |
| SOLOMONS LIMITED | 00998833 | 5010 |
| TRANSINTECH LIMITED | 02988561 | 3550 |
| TONG PARK LIMITED | 01837510 | 1730 |
| DE FACTO 681 LIMITED | 02478886 | 2451 |
| CH (UK REALISATIONS) LIMITED | 01989988 | 3110 |
| HOLLAS GARMENTS LIMITED | 00749446 | 1822 |
| AEC REALISATIONS LIMITED | 02841669 | 3162 |
| THURBER MANUFACTURING LIMITED | 01178722 | 3162 |
| QUEENSBURY INTERNATIONAL LIMITED | 02745165 | 3663 |

| | | |
|---|---|---|
| FAIRWAYS LIMITED | 02092882 | 5010 |
| LAWRENCE & STAMINA LIMITED | 00623655 | 1930 |
| OAKLAND FAIRFAX FURNITURE LIMITED | 03048753 | 9305 |
| MERRIOTT MOULDINGS LIMITED | 00344139 | 2524 |
| SCOTT (DUDLEY HILL) LIMITED | 00215217 | 1723 |
| THE WEISFELD PARTNERSHIP PLC | SC165824 | 5212 |
| ST MARY AT HILL NO.2 LIMITED | 02421608 | 3663 |
| KILLICK MARTIN & COMPANY LIMITED | 00524710 | 6340 |
| PCG GLASS LIMITED | 02434187 | 2612 |
| LB (1999) LIMITED | 01378819 | 2932 |
| LOGICAL NETWORKS LIMITED | 02280331 | 5170 |
| PEPPERL AND FUCHS LIMITED | 02609607 | 5170 |
| F.G. FINCH LIMITED | 00744159 | 4521 |
| HUTTON GROUP LIMITED | 02391679 | 4521 |
| REPOWER HOLDINGS LIMITED | 02894473 | 2875 |
| J LEESON AND CO LIMITED | 00431244 | 1772 |
| DOXEY ROAD LIMITED | 00154739 | 5153 |
| PRICE AND FINCH LIMITED | 00370046 | 1754 |
| PARAGON CARE GROUP LIMITED | 01864833 | 8511 |
| JOHN PARTRIDGE LIMITED | 01641514 | 5142 |
| N.E.C.A. HOLDINGS PLC | 01568690 | 2922 |
| ZONAL LIMITED | 00610655 | 2465 |
| A ONE TRANSPORT LIMITED | 00436463 | 6024 |
| REVELATION PICCADILLY HOLDINGS PLC | 03088728 | 5243 |
| TOUCHWOOD INDUSTRIES LIMITED | 02916263 | 3230 |
| NORDALE FOODS LIMITED | 02364956 | 7499 |
| SAFELINE (SCOTLAND) LIMITED | SC082827 | 5142 |
| HAUGHTON ENGINEERING INSURANCE SERVICES LIMITED | 01262000 | 7414 |
| NORWICH SPORT VILLAGE LIMITED | 01945514 | 9272 |
| ENGINEERING WITH EXCELLENCE HOLDINGS LIMITED | 02947934 | 2852 |
| HOLLAS HOSIERY LIMITED | 01005462 | 1771 |
| ROCKCHALK LIMITED | 02007104 | 2121 |
| MANSE WINDOW DESIGN LIMITED | 01996163 | 2051 |
| TIME TO INSURE LIMITED | 02688864 | 6603 |
| SPORTS MAX LIMITED | 03006148 | 5243 |
| VICKERS MEDICAL LIMITED | 00996819 | 8514 |
| WHITES OF TAUNTON LIMITED | 00538994 | 5010 |
| PRECIS (1746) LIMITED | 01292013 | 2466 |
| YAGS PLC | 02671596 | 5139 |
| ESPRIT (U.K.) LIMITED | 02044705 | 5142 |
| DANIEL PLATT (STOKE-ON-TRENT) LIMITED | 00206751 | 7499 |
| J.W.BRAITHWAITE & SON LIMITED | 00282436 | 2223 |
| THOMAS ASHWORTH AND COMPANY LIMITED | 00096204 | 2753 |
| THE BEST GROUP LIMITED | 02773488 | 3663 |
| WILSON AND STAFFORD LIMITED | 00032669 | 1824 |
| TRANSMERE DISTRIBUTION LIMITED | 02710458 | 6340 |
| TURSDALE ENGINEERING LIMITED | 02901495 | 2852 |
| CONSOLIDATED COAL PLC | 00350246 | 1010 |
| JOHN ROBERTS & SONS (LANGCLIFFE) LIMITED | 00351560 | 2112 |
| WEATHERGLAZE PLC | 02498853 | 4521 |
| NAIT PLC | 02236016 | 5010 |
| AMALGAMATED PLASTICS LIMITED | 00488367 | 2522 |
| FLORAL STREET PLC | 02693493 | 3663 |
| SIGNALFERN LIMITED | 01938467 | 1010 |
| SHOWPLA U.K. LIMITED | 02350131 | 2524 |
| CHADWICK WEB PROCESSING PLC | 03201362 | 9305 |
| BURN FIRECLAY COMPANY,LIMITED(THE) | 00313318 | 2640 |
| ST. MARTHA'S CARE SERVICES LIMITED | 02825861 | 9305 |
| POULTON LIMITED | 00678361 | 4525 |
| ERRUT INTERNATIONAL LTD | 02420752 | 2030 |
| STEWART MECHANICAL SERVICES PLC | 01160969 | 4533 |
| G. REID & SON LIMITED | SC021396 | 4521 |
| SCOTPRINT LIMITED | SC045424 | 2222 |
| GROSVENOR LIFESTYLE PLC | 03254128 | 9304 |
| REGGIO LIMITED | 02454389 | 2222 |
| MICRONAIR LIMITED | 00564960 | 2932 |
| APPLEWOODS INTERNATIONAL LIMITED | 02734659 | 3663 |
| CIRCLE 130 LIMITED | 00741506 | 4521 |
| BRITPLAS REALISATIONS LIMITED | 02743039 | 2524 |
| PERSHORE POULTRY LIMITED | 02476323 | 5132 |
| BIOS (CONSULTANCY & CONTRACT RESEARCH) LIMITED | 01204003 | 7310 |
| HUSBANDS LIMITED | 00346821 | 3511 |

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| RIGHT TRACK CONSTRUCTION LIMITED | 02778703 | 4521 |
| HOERBIGER SERVICE LIMITED | 00325864 | 2912 |
| KEY WINDOWS LIMITED | 01736420 | 4544 |
| VALORUM LIMITED | 01816330 | 7414 |
| PENTNEY ENGINEERING LIMITED | 02625925 | 2875 |
| SAROVA (RUBENS) LIMITED | 02805825 | 5511 |
| WEBSTER TOOLING LIMITED | 02315086 | 2852 |
| CHARLES HARBAGE LIMITED | 00242280 | 2940 |
| JOHN WILSON LIMITED | 00288616 | 5020 |
| CYBERDESK INTEGRATED SOLUTIONS LIMITED | 01316484 | 7220 |
| K.T. (DARTFORD) LIMITED | 00678560 | 5010 |
| RHODES INDUSTRIES LIMITED | 01701578 | 7499 |
| ATHENS AIR CATERERS LIMITED | 00691049 | 5552 |
| ST. DAVIDS NURSING HOME LIMITED | 01944421 | 8514 |
| BRITISH LEATHER COMPANY,LIMITED(THE) | 00089647 | 1910 |
| IRWIN-DESMAN LIMITED | 01400172 | 2852 |
| MICHAEL BUTLER LEATHER GOODS LIMITED | 00834272 | 1920 |
| H.WOOD & SONS(WHOLESALE GROCERS)LIMITED | 00534667 | 5211 |
| D REALISATIONS LIMITED | 01139057 | 2940 |
| JOHN WILSON (AUTOS) LIMITED | 01722259 | 5030 |
| TRANSTEC (KL) LIMITED | 00681931 | 3320 |
| CHASE TECHNOLOGY PLC | 03112216 | 7260 |
| D HOLDINGS REALISATIONS LIMITED | 03130730 | 7484 |
| BMMK GROUP LIMITED | 02109403 | 7420 |
| HEDGEBADGER LIMITED | 00041448 | 2924 |
| DAVIES BROS. (PENCADER) LIMITED | 00598564 | 6023 |
| WASHINGTON HOTEL LIMITED | 02701599 | 5511 |
| J.WALSH(FOOTWEAR)LIMITED | 00946774 | 1930 |
| EVERGREEN TRAVEL SERVICE LIMITED | 02614496 | 6330 |
| PLANAGEAR LIMITED | 00918944 | 2524 |
| CLIFFORD WHATMOUGH LIMITED | 00206540 | 2875 |
| COOKSON AND ZINN LIMITED | 01800558 | 2811 |
| RETYRED 99 LIMITED | 02516685 | 4010 |
| SPIKES CAVELL & COMPANY LIMITED | 02502826 | 7413 |
| GOWY FABRICATIONS LIMITED | 01365634 | 2811 |
| BRADFORD SOAP WORKS LIMITED | 02674893 | 2451 |
| PAUL WILSON PINE FURNITURE LIMITED | 02155729 | 3614 |
| OAKPARK GUARDING SERVICES LIMITED | 03073149 | 7524 |
| SOUTH KNIGHTON DYE WORKS LIMITED(THE) | 00211666 | 1730 |
| VDL ENGINEERING LIMITED | 02479359 | 2875 |
| CLAREMOUNT HOLDINGS LIMITED | 02360716 | 6603 |
| OCEAN P & I SERVICES LIMITED | 01792976 | 6603 |
| DOROTHEA GROUP LIMITED | 03003137 | 2875 |
| NHSW REALISATIONS LIMITED | 02998262 | 5272 |
| GRIST CONSTRUCTION LIMITED | 02517471 | 4521 |
| WOODCHOPPER ONE LIMITED | 03128101 | 6713 |
| SEATONS OF YEOVIL LIMITED | 03279889 | 5010 |
| DART SPRING LTD | 01973193 | 2873 |
| ANDREW BRYAN & CO. LIMITED | SC057430 | 4521 |
| STAR ENGINEERING PRODUCTS (SHREWSBURY) LIMITED | 02014646 | 2852 |
| MELTEK GROUP PLC | 02908576 | 7220 |
| THE LEADING EDGE (RETAIL) LIMITED | 02126713 | 5243 |
| BERKELEY CONSTRUCTION SERVICES LIMITED | 01545982 | 5114 |
| BROOKSIDE DYERS & FINISHERS LIMITED | 00947540 | 1730 |
| VICTOR CAST WARE LIMITED | 01685314 | 3663 |
| KEABEECH LIMITED | 02909287 | 9271 |
| F BIBBY & CO LIMITED | 00822686 | 5141 |
| HADRIAN PMC INTERNATIONAL LIMITED | 00945718 | 5243 |
| W B CHAMBERS & SON LIMITED | 00611444 | 0112 |
| GEECO LIMITED | 02378016 | 2524 |
| FINCH (GB) LIMITED | 02375129 | 4521 |
| FREQUENTGUIDE LIMITED | 02673147 | 6330 |
| COAST (1996) LIMITED | 02618725 | 5142 |
| SANDWICHKING (S.E.) LIMITED | 02994238 | 1533 |
| VALLEY INDUSTRIES LIMITED | 03232944 | 2524 |
| TRENT VALLEY GROWERS LIMITED | 02116273 | 0112 |
| GSJ (METEOR) LIMITED | 02074285 | 5010 |
| LYMDENE LIMITED | 02716173 | 1821 |
| NORTH TIMBER LIMITED | 02882633 | 2051 |
| FOUNDRY AND TECHNICAL LIAISON LIMITED | 00824036 | 3663 |
| SMITHGILL LIMITED | 01802689 | 4531 |
| SAM UK LIMITED | 02237901 | 7220 |

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| G R P FABRICATIONS LIMITED | 02839342 | 2524 |
| COMPANY 1521157 LIMITED | 01521157 | 2710 |
| SANTS PLC | 00278148 | 5146 |
| AUGAT LIMITED | 01220713 | 3162 |
| CARTEL INTERNATIONAL LIMITED | 00933506 | 5156 |
| STOLT SEA FARM LTD. | SC114037 | 0502 |
| JOHNSON BROTHERS (REDDITCH) LIMITED | 00543640 | 5010 |
| DAW ASSOCIATES LIMITED | 02193169 | 5010 |
| MAXPOWER (AUTO) LIMITED | 01700776 | 5030 |
| WARMCHECK LIMITED | SC140097 | 6024 |
| PITCOMP ABC LIMITED | 03088146 | 7484 |
| BELGRAVE ENGINEERING LIMITED | 02137206 | 2875 |
| TEDDINGTON BELLOWS LIMITED | 02139069 | 2811 |
| CONSPEED LIMITED | 01462991 | 5010 |
| TEAMHAWK DISTRIBUTION LIMITED | 02529448 | 6024 |
| CRAFTWORLD TRADING LIMITED | 03200452 | 5248 |
| TEXT SYSTEMS GROUP LIMITED | 03184849 | 5164 |
| ROE ROADS LIMITED | 00751874 | 4521 |
| HEADWEY (U.K) LTD. | 02689228 | 8042 |
| MERELAKE PLASTICS LIMITED | 01680376 | 7499 |
| M R J (DEMOLITION) LIMITED | 02783479 | 4511 |
| INS REALISATIONS LIMITED | 00858132 | 5170 |
| GRAND HOTEL MANAGEMENT LIMITED | 02425192 | 5511 |
| S.L.C. (AUTOMATION) LIMITED | 02065988 | 2922 |
| G.K.R. CONSTRUCTION LIMITED | 01484861 | 4521 |
| A & G PEARSON TRANSPORT LIMITED | 02850140 | 6024 |
| BEECH AVENUE HOMES LIMITED | 03017702 | 8514 |
| PAICE AND SONS LIMITED | 00454537 | 5170 |
| WANDSWORTH REALISATIONS NO 1 LIMITED | 00153960 | 4521 |
| SMILES TRADITIONAL INNS II PLC | 02859652 | 5540 |
| FOUNTAIN WAY LIMITED | 01025953 | 3162 |
| TRING INTERNATIONAL PLC | 02463393 | 5147 |
| FRANK STARKEY LIMITED | 00493587 | 1581 |
| FINEONE LIMITED | 02623467 | 9305 |
| ADVANTAGE HEALTHCARE (T12) LIMITED | 03424184 | 8511 |
| BODEN HOLDINGS LIMITED | 02183990 | 5010 |
| LARKFIELD OF CHEPSTOW LIMITED | 01310651 | 5010 |
| RGP COMPUTERS LIMITED | 01833909 | 5170 |
| SHEPHERDS SCRAP METALS (NEWCASTLE) LIMITED | 01479261 | 4525 |
| A. RIDDELL & COMPANY, LIMITED | 00201264 | 1822 |
| LIBRA GROUP LIMITED | 00742011 | 2222 |
| NOTTINGHAM ICE STADIUM LIMITED | 00620580 | 9272 |
| OFFSHORE ACCOMMODATION SERVICE LIMITED | 02439445 | 9305 |
| CUNLIFFE GRAVURE LIMITED | 00858339 | 2222 |
| MARCO BERNI HOTELS LIMITED | 01017098 | 5511 |
| ULTRASEAL INTERNATIONAL LIMITED | 01928420 | 2466 |
| PALMGRADE PLC | 01633621 | 3220 |
| CRISPINS (RESTAURANTS) LIMITED | 02659956 | 5530 |
| EURO-WEST DISTRIBUTION LIMITED | 02737450 | 3162 |
| TEIN PLC | 01041119 | 6512 |
| CLEALES,LIMITED | 00444510 | 5010 |
| DAVID NUNN LIMITED | 01080372 | 5111 |
| JOHN CLELAND (LONDON) LTD. | 00560551 | 2121 |
| T. WRIGHT LIMITED | 00270806 | 5134 |
| S. LEE MANUFACTURING LIMITED | 01372226 | 1824 |
| VALORUM (EUROPE) LIMITED | 02343142 | 7310 |
| DIBDEN PURLIEU MOTORS LIMITED | 01437689 | 5010 |
| GRAYCORN ASSOCIATES LIMITED | 02659884 | 2222 |
| NORDICTRACK (U.K.) LTD | 02672137 | 9272 |
| TRING INTERNATIONAL GROUP PLC | 02870056 | 5147 |
| MASONPOINT GROUP LIMITED | 02617117 | 2852 |
| SMILES TRADITIONAL INNS PLC | 02792459 | 5540 |
| MEMSOLVE LIMITED | 03047790 | 7260 |
| ENDULTRA LIMITED | 02799684 | 7484 |
| BRITISH SOAP COMPANY LIMITED | 01093728 | 2451 |
| ROGERSONS LIMITED | 01040178 | 4521 |
| J.C.S. TRAINING SERVICES LIMITED | SC124967 | 7484 |
| TR GROUP (HOLDINGS) LIMITED | 02441226 | 6024 |
| M + N (CABLE AND INSTALLATION) LIMITED | 02644271 | 4531 |
| WARLEY CONTINENTAL SERVICES LIMITED | 01573302 | 5010 |
| BRIATON LIMITED | 02750177 | 9305 |
| CHPL REALISATIONS LIMITED | 03074991 | 5132 |

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| STEWART-WARNER INSTRUMENTS LIMITED | 03184411 | 2852 |
| HOLBRUCK PRODUCTS LIMITED | 01490380 | 2874 |
| S WOOD REALISATIONS LIMITED | 01582567 | 3614 |
| J.C. TIMBERS LIMITED | 01706695 | 7499 |
| MAURICE JACQUES LIMITED | 00759085 | 1823 |
| ZOO CORPORATION PLC | 02335183 | 9305 |
| PONTYPRIDD PALLET COMPANY LIMITED | 01587807 | 2040 |
| GALLBROS CIVIL ENGINEERING LIMITED | 03114561 | 4521 |
| PULLEYN HOLDINGS LIMITED | 01505947 | 2040 |
| A.J. FRYER & CO. LIMITED | 00456334 | 5010 |
| ADEPT ELECTRONICS LIMITED | 02479627 | 3162 |
| STEVEN & KEITH LIMITED | 00853028 | 2416 |
| UNIQUEMERGE LIMITED | 01883647 | 9999 |
| HAMSUDD 2002 LIMITED | 02382726 | 3110 |
| GROSVENOR CARE PLC | 02226059 | 8514 |
| BANK AUSTRIA CREDITANSTALT FUTURES LTD | 02640617 | 6523 |
| MECHS PRODUCTION SERVICES LIMITED | 02315849 | 7440 |
| FUTOO LIMITED | 03020232 | 2875 |
| BEAVER PIPEWORK SERVICES LIMITED | 03111042 | 2811 |
| R CORBEN & SON (HOLDINGS) LIMITED | 00255551 | 4521 |
| LEE FARM EGGS (YORKS) LIMITED | 01837298 | 5139 |
| KIRBY'S CONVERTING MACHINERY LIMITED | 02835399 | 2955 |
| CORBEN CONSTRUCTION LIMITED | 00867818 | 4521 |
| M.R.J. PHILLIPS (METALS) LIMITED | 01784795 | 5157 |
| FULTON MOTORS LIMITED | 00849678 | 5010 |
| GSH (METEOR) LIMITED | 02050790 | 5010 |
| Z PRODUCTS LIMITED | 02409259 | 2924 |
| R.D. INTERNATIONAL (U.K.) LIMITED | 02482955 | 7420 |
| MERLIN MANUFACTURING LIMITED | 02661625 | 1822 |
| COVPAK LIMITED | 00834266 | 2121 |
| DAVID FISHER & SONS (EDINBURGH) LIMITED | SC041192 | 4541 |
| J.R.NEYLAND MOTORS LIMITED | 00629042 | 5010 |
| METRAKING IMPROVEMENTS GROUP PLC | 00800303 | 7414 |
| MONTAGUE F UPTON LIMITED | 00996811 | 7484 |
| EUROPA SCIENTIFIC LIMITED | 01919580 | 3320 |
| KINGCUP MUSHROOMS LIMITED | 01180848 | 0112 |
| SEAFRESH FOODS LIMITED | 02402823 | 1520 |
| SMIS LIMITED | 01875407 | 3320 |
| BICERI LIMITED | 02642355 | 7310 |
| INNER WORKINGS LIMITED | SC135299 | 3002 |
| NEBRASKA GROUP OF COMPANIES LIMITED | 02898901 | 5245 |
| INNER WORKINGS GROUP PLC | SC157430 | 9231 |
| NORBERT DENTRESSANGLE CONTINENTAL LIMITED | 03047920 | 6024 |
| PANTHEON HOTELS AND LEISURE LIMITED | 01566794 | 5511 |
| PAD & PAPER LIMITED | 01410861 | 2121 |
| FIRST INNOVATIONS LIMITED | 01639507 | 7220 |
| CAPITAL REPROGRAPHICS LIMITED | 02141906 | 7484 |
| F. SNELSON & SON LIMITED | 01385087 | 5132 |
| NIWEL GROUP LIMITED | 00970986 | 4521 |
| INSTANTSCORE LIMITED | 02818925 | 5142 |
| MERCANTILE COMMUNICATIONS LIMITED | 02797733 | 6420 |
| CHRISTOPHER HADYN LIMITED | 01689049 | 1824 |
| HEWITT OF SUNBURY LIMITED | 00563462 | 5010 |
| SARAT LIMITED | 01260785 | 7481 |
| STAIR TREAD SUPPLY CO. LIMITED | 01151532 | 7499 |
| EADE PIPELINES LIMITED | 01352707 | 4100 |
| HASTINGS PIER COMPANY LIMITED | 01934373 | 5530 |
| HAREB GROUP PLC | 01971401 | 2852 |
| ROLDEC SYSTEMS PLC | 02490072 | 7220 |
| I.E.S. INSTRUMENTATION AND ELECTRICAL CONSTRUCTION SERVICES LIM | 01919863 | 4525 |
| CLARKE & SMITH MANUFACTURING COMPANY LIMITED(THE) | 00436282 | 3230 |
| OVERLANDER TRAILERS LIMITED | 00489986 | 2852 |
| SUNTEX FORMTEX PLASTICS LIMITED | 01258394 | 2416 |
| ROLECY LIMITED | 01394136 | 5170 |
| DERNIE CONSTRUCTION LIMITED | 01190267 | 4521 |
| N.E.C. ENGINEERING LTD. | 02287385 | 2852 |
| PUBLISHING DISTRIBUTORS INTERNATIONAL (UK) LIMITED | 02861923 | 7414 |
| THE HOUSE OF DE PARYS LIMITED | 03010090 | 9301 |
| VIDEO TELE SALES LIMITED | 02133679 | 5212 |
| IT & T COMMUNICATIONS LIMITED | 02456954 | 6420 |
| BAYMARK LIMITED | 01694342 | 3612 |
| BUTLERS CATERING (LONDON) LIMITED | 02968458 | 5552 |

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| PERSONAL COMPUTER SCIENCE LTD | 03045904 | 3002 |
| CRANBROOK ELECTRONIC HOLDINGS LIMITED | 01507697 | 5165 |
| LINSEC 506 LIMITED | 02012106 | 7220 |
| PEEL DIECASTING LIMITED | 02072806 | 2753 |
| CENTRAL ENGLAND TEC | 02453206 | 9305 |
| BARRETT CONSTRUCTION LIMITED | 01544780 | 4521 |
| CAMBUS LITHO LIMITED | SC045384 | 2222 |
| THE BRIARY HOME PLC | 02458904 | 8514 |
| JODEN INTERNATIONAL UK LIMITED | 03021303 | 3661 |
| BATSFORD HOLDINGS LIMITED | 01560333 | 6523 |
| BTB REALISATIONS LIMITED | 00132704 | 2211 |
| OTRA E LIMITED | 01358428 | 5170 |
| THE VENDING AND CATERING COMPANY PLC | 00977003 | 5118 |
| WILLIAM OSBORNE,LIMITED | 00287699 | 3511 |
| BILL HUTCHINSON LIMITED | SC083661 | 5245 |
| PARKSIDE CLINIC LIMITED | 01101135 | 8514 |
| TOWERCLIFF LIMITED | 02529071 | 5010 |
| CJSE REALISATIONS LIMITED | 02577923 | 4531 |
| KITEBETA LIMITED | 01174953 | 5010 |
| NORMAN CORDINER LIMITED | SC131297 | 5010 |
| PMC ELECTRONICS LIMITED | 01810662 | 3162 |
| RUSJON LIMITED | 01136422 | 4521 |
| YAMAICHI BANK (U.K.) PLC | 01980369 | 6512 |
| ACORN FASHIONS LIMITED | 02858172 | 1824 |
| NEW JAPAN SECURITIES EUROPE LIMITED | 01324694 | 6523 |
| RONALD JOYCE (LONDON) LIMITED | 01678376 | 1824 |
| S.RUSSELL & SONS MANUFACTURERS LIMITED | 01008752 | 1822 |
| STONE CO-ORDINATED CERAMICS LIMITED | 01523863 | 2625 |
| PAUL GROUP INTERNATIONAL (INSURANCE BROKERS) LIMITED | 02625931 | 6601 |
| APS GEARS LIMITED | 02900619 | 2852 |
| MASTERS & MILBURN SQUARE DEAL GARAGE LIMITED | 01410326 | 5010 |
| FORM FILL SEAL LIMITED | 01929976 | 7482 |
| ATLAS PRODUCTS INTERNATIONAL LIMITED | 01458001 | 7220 |
| LION SECURITY SERVICES (UK) LIMITED | 03145557 | 7460 |
| GOLDING PIPEWORK SERVICES LIMITED | 01436250 | 4525 |
| QUINTECH COMPUTER SERVICES LIMITED | 01520303 | 7220 |
| PLUSLONE INDUSTRIES PLC | 02225078 | 1822 |
| BELLS BRISTOL LIMITED | 02769612 | 2875 |
| MMT COMPUTING (READING) LIMITED | 01902771 | 7220 |
| THE HOUSE LIMITED | 02801815 | 3663 |
| PARRETT & NEVES,LIMITED | 00088029 | 2222 |
| ZENYX SCIENTIFIC LIMITED | 01113385 | 3320 |
| NORWICH SPORT VILLAGE (MANAGEMENT) LIMITED | 02454392 | 7011 |
| BEN BLOOM (LONDON) LIMITED | 00474222 | 1822 |
| PERFECT ENTERTAINMENT LIMITED | 01937891 | 7220 |
| BRISTOL RUGBY FOOTBALL CLUB LIMITED | 03191555 | 9261 |
| HYTEX DUO LIMITED | 02552760 | 2513 |
| THAMESDOWN CARER RELIEF LIMITED | 01589026 | 8532 |
| ZONAL AUDIO PLASTICS LIMITED | 02322254 | 3663 |
| BRISTOL ENVELOPES LIMITED | 02681625 | 2123 |
| FOUR POINT HIRE LIMITED | 00592766 | 6024 |
| HARBORNE GROUP LIMITED(THE) | 01257305 | 5010 |
| WAHLCO ENGINEERED PRODUCTS LIMITED | 00526365 | 2875 |
| SURGETROLL LIMITED | 02000142 | 2852 |
| WILSON WILCOX FURNISHINGS LIMITED | 02377439 | 5147 |
| MAXCOM PLASTICS LIMITED | 01525525 | 2524 |
| SOCIETE GENERALE EQUITIES INTERNATIONAL LIMITED | 02686296 | 6523 |
| BULPHAN LIMITED | 01325483 | 4531 |
| EUROPASTYLE LIMITED | 02761482 | 5142 |
| GROUP ACUITY LIMITED | 02614359 | 7220 |
| THE BIRMINGHAM MULTI-FUND COMMITTEE | 02810258 | 7414 |
| DEVERON ENVIRONMENTAL LIMITED | SC115251 | 7484 |
| GOLD STAR (NATURAL FRUIT JUICES) LIMITED | 02896161 | 1598 |
| PIPEWORK INTERNATIONAL LTD. | 02775632 | 4525 |
| DEVERON GROUP LIMITED | SC156415 | 4100 |
| WELLS NURSING HOME LIMITED | 02028935 | 8514 |
| BEADLOW MANOR PLC | 02492788 | 5511 |
| MIDLAND GRANULATORS LIMITED | 01999009 | 5157 |
| UNIQUE CUISINE LTD. | SC154607 | 1533 |
| JAMES CAFFERY & SONS LIMITED | 00531073 | 6024 |
| NHCA REALISATIONS LIMITED | 01896211 | 5272 |
| KEW GROUP LIMITED | 02821039 | 1717 |

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| THE VICTORIA HOTEL COMPANY (BRADFORD) LIMITED | 02940254 | 5511 |
| FATROE LIMITED | 02764386 | 7484 |
| SQUARE SCISSORS LIMITED | 02729846 | 7220 |
| GRIMLIEW LIMITED | 01643260 | 5142 |
| WILSON PURVES LIMITED | 00736107 | 5010 |
| GAYDON PRESS LIMITED | 01998630 | 2222 |
| WENTING TEXTILES LIMITED | 01971522 | 1823 |
| A B TRAINING LIMITED | 01927347 | 9305 |
| EBIG PLC | 01036034 | 7484 |
| FULSHAW FARMS PRODUCTS LIMITED | 01386084 | 1551 |
| UNIPOL POLYTHENE INDUSTRIES LIMITED | 02669419 | 2524 |
| WBS BROOKS LIMITED | 02705291 | 5170 |
| D. HENNELLY PLANT HIRE LTD. | 03051358 | 4550 |
| ANDREW GOLIGHTLY LIMITED | 01395897 | 1450 |
| MATRIX PRINTING FOR BUSINESS LTD | 01840534 | 2222 |
| REDMAN MECHANICAL & ELECTRICAL SERVICES LIMITED | 02210435 | 4521 |
| PLANIT TRAVEL LIMITED | 02592561 | 6330 |
| NATIONAL CARE CALL LIMITED | 02693758 | 7499 |
| DINTON NURSING HOME LIMITED | 01459449 | 8514 |
| EUROTECH DEVELOPMENT LIMITED | 03138134 | 7484 |
| W HOSP & CO LIMITED | 02954473 | 5133 |
| AUSTIN, PERKS & HALL LIMITED | 00452999 | 2875 |
| PC SECURITY LIMITED | 02029513 | 7220 |
| PACKAGING (REALISATIONS) LIMITED | 00969306 | 2040 |
| THE PATERNOSTER PARTNERSHIP LIMITED | 02732685 | 7413 |
| JOHN THOMLINSON LIMITED | SC007337 | 2121 |
| CASTAL (1986) LIMITED | 01987809 | 2742 |
| DIPLOMAT PROFILES (U.K.) LIMITED | 01999398 | 9305 |
| DRIVE FOR YOUTH PROGRAMME LIMITED | 01988406 | 8531 |
| HAYDONS LIMITED | 02070896 | 5147 |
| BUCHANAN PARTNERS LIMITED | 02438831 | 7484 |
| D B S (CROWBOROUGH) LIMITED | 02595465 | 5010 |
| PILOTLINK LIMITED | 02784659 | 2213 |
| BUSINESS LINK SANDWELL LIMITED | 03005222 | 7484 |
| DCE COMMUNICATIONS GROUP PLC | 00973639 | 3220 |
| J P FIELDING & CO LIMITED | 01413765 | 9305 |
| WHITES OF BRIDGWATER LIMITED | 00485995 | 5010 |
| ARTHUR E. COOK (CROYDON) LIMITED | 00862890 | 4531 |
| MARKHAM HB LIMITED | 00801281 | 7484 |
| BULLER PLASTICS LIMITED | 00801098 | 1930 |
| LGC NO 7 LIMITED | 02840530 | 7260 |
| NUCLEUS CREATIVE SERVICES LIMITED | 02749302 | 7481 |
| C.M.B. ENGINEERING LTD | 02717067 | 2710 |
| DATA PRESS MANUFACTURING LIMITED | 02778039 | 2222 |
| PACESETTER MEDICAL PRODUCTS LIMITED | 02943559 | 3310 |
| JAFFE KEATING LTD | 02604116 | 6523 |
| M & N CIVIL ENGINEERING LIMITED | 02903168 | 4525 |
| CASTLE BUSINESS SERVICES LIMITED | 03064374 | 8021 |
| MONIFIETH HOTEL LIMITED | SC061122 | 2513 |
| AVENIR (UK) LIMITED | 03240700 | 7220 |
| DUNCAN ADVANCED PLC | SC161672 | 3162 |
| MAYCLIFF LIMITED | 03194132 | 2513 |
| S & B MOTOR CYCLES LIMITED | 01041528 | 5010 |
| EURIBON GROUP PUBLIC LIMITED COMPANY | 01814666 | 5170 |
| HILLYERS BAKERIES LIMITED | 00598831 | 5224 |
| MELA COMPUTERS LIMITED | 02355132 | 7220 |
| PARK FABRICS (LEICESTER) LIMITED | 02358691 | 1740 |
| UNIVERSAL INTERNATIONAL PLC | 01166447 | 5170 |
| PRIMA ASSOCIATES (EC) LIMITED | 02540200 | 5170 |
| DUAL CARRIAGE LIMITED | 02831337 | 6024 |
| LONG CLOSE SCHOOL LIMITED | 00817979 | 8021 |
| MANOR NURSING HOMES LIMITED | 02739370 | 8514 |
| COMPLETE CIVIL CONTRACTS LIMITED | 03289739 | 4521 |
| G A WOODCOCK FREIGHT (REALISATIONS) LIMITED | 00943169 | 6024 |
| BREADSALL DEVELOPMENTS LIMITED | 01758579 | 4523 |
| DARMAN & VONIELJOF LIMITED | 02346052 | 5132 |
| FORM-ALL LIMITED | 02194250 | 2875 |
| PRIMROSE WALLCOVERINGS LIMITED | 01889663 | 2124 |
| OLYMPIA (UK) LIMITED | 02355936 | 5170 |
| CD REVOLUTION LIMITED | 02696258 | 5143 |
| COVERPLUS (PROOFINGS) LIMITED | 02270855 | 1717 |
| GOLDEN VALLEY SHOES LIMITED | 02655667 | 1930 |

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| CRAFTWOOD LTD | 02379952 | 4542 |
| PRESTIGE ACCIDENT MANAGEMENT SERVICES LIMITED | 02490323 | 6603 |
| RODING RIVER FOUNDRY LIMITED | 00467256 | 2875 |
| DARTFORD SELECTION LIMITED | 03135195 | 7450 |
| FERNLEA HOUSE LIMITED | 03011807 | 7420 |
| FINANCIAL DATABASE MARKETING LIMITED | 02871806 | 9305 |
| OPTIMISE INFORMATION (UK) LIMITED | 02913349 | 9305 |
| SNUGCHIEF LIMITED | 02108863 | 5530 |
| EURIBON LIMITED | 01244627 | 7220 |
| PET FEEDS LIMITED | 02642661 | 1571 |
| U.K. MAINTENANCE LIMITED | 01959098 | 4521 |
| T.H.SUTCLIFFE (MEAT WHOLESALERS) LIMITED | 01015549 | 5132 |
| ARIATON LIMITED | 02604115 | 9305 |
| CHASLEY HOTELS TORBAY LIMITED | 03105950 | 5511 |
| SOUTHERN MEADOW DAIRY (PINNER) LIMITED | 02832578 | 1551 |
| KANKAKU (EUROPE) LIMITED | 01388814 | 6523 |
| TOYO TRUST INTERNATIONAL LIMITED | 01775926 | 6523 |
| VIBRAFLO LIMITED | 00922299 | 2922 |
| AMEREX STEEL LIMITED | 02305604 | 5170 |
| GEOFFREY BASKIND LIMITED | 01338596 | 5231 |
| ICS IDENTCODE SYSTEMS GB LIMITED | 01850636 | 7220 |
| PARGAS CONSTRUCTION LIMITED | 00519398 | 4521 |
| N.J.GROSE LIMITED | 00676148 | 6024 |
| CHALON PRESS LIMITED | 01839716 | 2222 |
| CREOS LIMITED | SC114956 | 3162 |
| PORTLAND CLOTHING LIMITED | 02618723 | 5142 |
| EXCEL AIR SYSTEMS LIMITED | 02679895 | 4533 |
| J.B. PRODUCTS (MIDLANDS) LTD | 01357130 | 4525 |
| COMART S.M.S. COMPUTER MAINTENANCE LIMITED | 02963486 | 7220 |
| SUMADA ENGINEERING LIMITED | 01064901 | 2513 |
| A. H. (1998) LIMITED | 00075368 | 2940 |
| AEROSPACE METALS LIMITED | 01284797 | 2875 |
| DAIRY SUPPLIES(HEREFORD)LIMITED | 00597081 | 5114 |
| BRICEY LIMITED | 01602210 | 7484 |
| NEWPAR PRESS LIMITED | 00959656 | 2222 |
| ALPHA ELECTRONICS PUBLIC LIMITED COMPANY | 01763658 | 3162 |
| CBI EDUCATION FOUNDATION(THE) | 01261991 | 9305 |
| GEO-RESEARCH LIMITED | 00749195 | 4521 |
| CHARLES HARBAGE METALS LIMITED | 02814108 | 5170 |
| CONNEXE PERIPHERALS LIMITED | 02786676 | 9305 |
| MISOMEX ENGINEERING LIMITED | 02607346 | 2940 |
| MAPOURIKA LIMITED | 02697343 | 7484 |
| ETCH LINE LIMITED | 02955537 | 3663 |
| MOSSHALL PRECISION LIMITED | SC154804 | 2811 |
| WORLDGATE LIMITED | 03190485 | 7260 |
| PRONTO ELECTRONICS LIMITED | 01081707 | 5156 |
| TAKEWORD TWO LIMITED | 02253781 | 2924 |
| HOWARTH BROTHERS HAULAGE(OLDHAM)LIMITED | 00875582 | 6024 |
| NIGEL COUCH PRODUCTIONS LIMITED | 00842606 | 1581 |
| NEW INVENTION MOTOR SERVICES LIMITED | 00596385 | 5010 |
| NORBERT DENTRESSANGLE TANKERS (1995) LIMITED | 02676956 | 6024 |
| KENSINGTON PLAZA HOTEL LIMITED | 01113980 | 7020 |
| DRUID CROWN TECHNOLOGY PUBLIC LIMITED COMPANY | 02813335 | 3002 |
| C G Z LIMITED | 02367945 | 4544 |
| SHANNON ENGINEERING LIMITED | 02950476 | 2852 |
| CRAFTWORLD HOLDINGS PLC | 03138167 | 5248 |
| CLIFTON BARMOTT LIMITED | 00659751 | 2222 |
| JESS B.WOODCOCK & SON LIMITED | 00525496 | 6024 |
| MELTEK DATA LIMITED | 01676708 | 9305 |
| RCT REALISATIONS LIMITED | 00418872 | 2852 |
| THEATRE CURTAINS & CARPETS LIMITED | 00393822 | 5147 |
| COMAC INTERNATIONAL PLC | 01596984 | 7220 |
| HOME LIFE PRODUCTS LIMITED | 02052372 | 5170 |
| STC DIVIDENDS LIMITED | 00210615 | 2640 |
| ROMAC CIVIL ENGINEERING LIMITED | 02656302 | 4521 |
| DEAN PARK (SALES) LIMITED | 00974832 | 7011 |
| PRECEPT INTEGRATED DESIGN & MARKETING LIMITED | 02159008 | 7440 |
| BERNETT CATERING LIMITED | 02811244 | 5552 |
| REPORTING MATTERS LIMITED | 02699488 | 2222 |
| ST. JOHN'S HOME FOR THE ELDERLY LIMITED | 02662092 | 5511 |
| ASTON PERSONNEL LTD. | 02646486 | 9305 |
| CRINGLE CORPORATION LIMITED | 00413150 | 7011 |

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|---|---|---|
| ELECTRON CONTROL SYSTEMS LIMITED | 02015962 | 4531 |
| RAEMOIR HOTEL LIMITED | SC022468 | 5511 |
| THE PETROLEUM SCIENCE AND TECHNOLOGY INSTITUTE | SC120900 | 7310 |
| COWANS FABRICS LIMITED | 00657510 | 5241 |
| CORMLOW LIMITED | 02854099 | 1822 |
| ALLAN HOUSE LIMITED | SC099471 | 5511 |
| D.P. ADVISERS LIMITED | 01673964 | 7220 |
| SPORT STORES LIMITED | 02732710 | 5248 |
| D. COZENS LIMITED | 03141474 | 2513 |
| MOFFAT SOLUTIONS LIMITED | 03119105 | 7512 |
| OPTIPRECISION LIMITED | 03057078 | 3340 |
| ADELPHI CONSTRUCTION LIMITED | 03311217 | 3612 |
| ALEXANDER KITCHENS LIMITED | 03132395 | 5244 |
| LEWIS & PEAT (RUBBER) LIMITED | 00528621 | 7484 |
| JAYWELL JOINERY LIMITED | 01458146 | 4542 |
| AIRWAVE GLIDERS LIMITED | 01481346 | 3650 |
| BEIRNE & WATTS LIMITED | 01503755 | 5231 |
| WILLIAM GERARD LIMITED | SC040061 | 4521 |
| CHAWTON END GARAGE LIMITED(THE) | 00340151 | 5010 |
| MORGAN AFTERMARKET-SERVICE LIMITED | 00787854 | 5010 |
| ALSECURE LIMITED | 03000891 | 2875 |
| ROLLFORM FABRICATIONS LIMITED | 03008610 | 2875 |
| THE MERRY MILLER LIMITED | 03037195 | 2513 |
| LYNFOX (APD) LIMITED | 03043723 | 4525 |
| SHAFTFIELD FABRICATIONS LIMITED | 02940078 | 2875 |
| COMAC SYSTEMS (EUROPE) LIMITED | 02070309 | 7220 |
| HSBC GREENWELL | 01915770 | 6523 |
| STEPHEN PALMER LIMITED | 02197001 | 5010 |
| ACORN STUDIOS PLC | 01607025 | 7484 |
| AUTONES LIMITED | 00766437 | 9305 |
| M. & I. PLANT SERVICES LIMITED | 02107800 | 9305 |
| D.P. BURKE LTD. | 02308776 | 4521 |
| LOGITRON HOLDINGS PLC | 03070493 | 7260 |
| NURAS LIMITED | 03073405 | 7484 |
| PACKABLIST PLC | 01953856 | 2522 |
| WATLING MANAGEMENT LIMITED | 02295407 | 9305 |
| PHILIPPINE NATIONAL BANK (EUROPE) PLC | 02939223 | 7499 |
| GREENINGS LIMITED | 00072470 | 2875 |
| F O REALISATIONS LIMITED | 02569301 | 6024 |
| PHOTOSCRIPT GROUP LIMITED | 02091558 | 7220 |
| ATLANTA ENTERPRISES LIMITED | 02590734 | 5030 |
| CORLYN CONTRACTORS LIMITED | 01046081 | 4521 |
| PITCHMATCH LIMITED | 02602656 | 9305 |
| KARLINE SECURITY SYSTEMS PLC | 02301661 | 9305 |
| NEARHIKE LIMITED | 02816775 | 7220 |
| THE RESIDENCES AT MANCHESTER LIMITED | 02703933 | 7011 |
| APLIX PLC | 02592678 | 7415 |
| LIBRIS COMPUTING LIMITED | SC142665 | 7220 |
| QUIDS-IN (NORTH WEST) LIMITED | 02667020 | 7499 |
| WEBSTER (COMPOSITE) MOULDINGS LIMITED | 01736747 | 2524 |
| ELLESMERE PORT WAREHOUSING LIMITED | 02768106 | 9305 |
| MORTIMER CHARLES GROUP PLC | 03106524 | 7450 |
| RUGARTH HOLDINGS LIMITED | 03277966 | 7011 |
| AYZED LIMITED | 00362887 | 1822 |
| DAWSON ODAL LIMITED | 00377203 | 4521 |
| HARVEY GOLDSMITH ENTERTAINMENTS LIMITED | 01245513 | 9231 |
| MORRIS HANBURY JACKSON LE MAY LIMITED | 00689166 | 5139 |
| P.P. CONTROLS LIMITED | 01222944 | 5143 |
| TGW LIMITED | 00432586 | 2524 |
| ENCON MECHANICAL SERVICES LIMITED | 02063714 | 7484 |
| GOLDEN OCEAN (U.K.) LIMITED | 01493735 | 6340 |
| NORRIS JOINERY LIMITED | 01104721 | 2010 |
| P.T.W. MOULDINGS LIMITED | 01538944 | 2524 |
| SOUND DEVELOPMENTS STUDIOS LIMITED | 01870550 | 9231 |
| ELDAIR ENGINEERING LIMITED | 01634265 | 4531 |
| ULTIMA SYSTEMS INTEGRATION LIMITED | 02306241 | 7499 |
| EAST HILL GARAGE (CORNWALL) LIMITED | 02073910 | 5010 |
| SHARPNET PLC | 01640523 | 2212 |
| MRJ (RECYCLING) LIMITED | 02879425 | 5157 |
| GROUNDSCAPE MANAGEMENT SERVICES LIMITED | 02765668 | 0141 |
| PHILIP CHANDLER & CO. LIMITED | 02495564 | 7484 |
| STAINLESS SOFTWARE LIMITED | 02956261 | 7220 |

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|---|---|---|
| WILLENHALL CONSTRUCTION LIMITED | 03102553 | 4521 |
| CONSTABLE GROUP PLC | 03006387 | 5170 |
| F.STRIVENS & SON LIMITED | 00605154 | 5132 |
| NEW WSB LIMITED | 00169887 | 2413 |
| REGMA (U.K.) LIMITED | 01087320 | 5170 |
| COLBURN FRENCH & KNEEN (HOME) LIMITED | 02535103 | 6601 |
| GENASYS II LIMITED | 02197403 | 5170 |
| GILLEADE AND ASHWORTH LIMITED | 01390597 | 1930 |
| BIFFU LTD | 02672984 | 5010 |
| FAIRWAYS MAIDSTONE LIMITED | 02792041 | 5010 |
| ENGLISH & AMERICAN SERVICE COMPANY LIMITED | 02796317 | 6720 |
| INSTITUTE OF RENT OFFICERS AND RENTAL VALUERS | 03048460 | 2513 |
| WEST END BUILDING SERVICES LIMITED | SC148184 | 4521 |
| INHOCO 845 LIMITED | 03129502 | 4521 |
| THE ROYAL NAVY SUBMARINE MUSEUM | 03180028 | 9252 |
| MELBOURN PROPERTY COMPANY LIMITED | 00651342 | 4521 |
| T.P. HILL (CASTINGS) LIMITED | 01249710 | 3663 |
| ASAHI FINANCE (U.K.) LTD. | 02045606 | 6523 |
| MALLARDHAVEN LIMITED | 01700927 | 4525 |
| SOLAR OFFSET LIMITED | 01890419 | 9305 |
| THE HENRY MOORE SCULPTURE TRUST | 01708662 | 2513 |
| WAYNE GRAHAM MACHINERY LIMITED | 02353518 | 5170 |
| RHODES TOOLS LIMITED | 02726768 | 2862 |
| UTILITY CONSULTANTS INTERNATIONAL LIMITED | 02661690 | 9305 |
| BARROW-IN-FURNESS ASSOCIATION FOOTBALL CLUB LIMITED(THE) | 00099142 | 9261 |
| TRIBUNE FINANCIAL SERVICES LIMITED | 02684193 | 6713 |
| TRIBUNE MANAGEMENT SERVICES LIMITED | 02677103 | 7484 |
| LAVA SYSTEMS (EUROPE) LTD | 02818287 | 7220 |
| NODANA LIMITED | 01551604 | 9305 |
| SEALAND QUALITY FOODS SUBSIDIARY LIMITED | 02991012 | 5139 |
| VIKING PRESS LIMITED | 02922991 | 2222 |
| DEBTEX LIMITED | 03139363 | 1754 |
| FRENKEL TOPPING STRUCTURED SETTLEMENTS LIMITED | 02525306 | 7499 |
| S.A. WATTS (ALUMINIUM) LIMITED | 02039974 | 2875 |
| ROCKEDGE LIMITED | 03179397 | 5530 |
| MISOMEX UK LIMITED | 01775761 | 5170 |
| FOREST BUREAU PROPERTY MANAGEMENT SERVICES PLC | 00873826 | 7031 |
| BUSINESS ADDRESS LIMITED | 01963775 | 7440 |
| EGGINTON JUNCTION LIMITED | 01929533 | 3710 |
| KASTEN CHASE APPLIED RESEARCH LIMITED | 02764102 | 3220 |
| WOLVERHAMPTON CITY CHALLENGE | 02783466 | 9305 |
| EMAP ONLINE LIMITED | 01544558 | 7499 |
| EXPORAMA SYSTEMS LIMITED | 02705635 | 7484 |
| HOW MUSHROOMS LIMITED | 02998967 | 1533 |
| INDUSTRIAL & MARINE SALES LIMITED | 02839385 | 2875 |
| PRESS LINE LIMITED | 02744085 | 9305 |
| CENTRAL HOUSING SERVICES LIMITED | 03152043 | 5274 |
| CROFTBOUND LTD | 03154102 | 7484 |
| MELLING HOTELS LIMITED | 03075135 | 5511 |
| REVOLUTION ENVIRONMENTS LIMITED | 03005330 | 9305 |
| S & D DE GENEVA PLC | 03164950 | 7414 |
| PE & CO LIMITED | 00387380 | 5132 |
| ALMA GROUP LIMITED | 02424866 | 5142 |
| BEECHDALE HOMES (NORTHWEST) LIMITED | 02015166 | 4521 |
| VINCENT NALLY (CIVIL ENGINEERING) LIMITED | 01717599 | 4521 |
| AXON VETERINARY LIMITED | SC084461 | 7220 |
| BIBBY TANK CONTAINERS LIMITED | 01616316 | 6340 |
| DAYRISE LIMITED | 02425554 | 6330 |
| RUSSELL H. HAM LIMITED | 00820909 | 5010 |
| SYDNEY A.SMITH & COMPANY(LEEDS 1928)LIMITED | 00229400 | 1822 |
| THE ALLIED ENTERTAINMENTS GROUP LIMITED | 01819706 | 9220 |
| FORUM PRODUCTIONS LIMITED | 01733897 | 2222 |
| THRESHOLD LIMITED | 01672800 | 9305 |
| GUY CURTIS (1993) LIMITED | 02814110 | 5142 |
| ST. DAVIDS NURSING HOME (ANNEXE) LIMITED | 01944420 | 8514 |
| ONYX LIMITED | 02493716 | 7220 |
| AEROFREIGHT CARGO LIMITED | 02890396 | 6340 |
| EUROPRIME FASHIONS LIMITED | 02759950 | 1822 |
| M.A.C. LOAMS LIMITED | 01333329 | 9305 |
| SOLAR DIGITAL ORIGINATION LIMITED | 02627563 | 2222 |
| AMSTEEL SECURITIES (FAR EAST) LIMITED | 02113043 | 6712 |
| CANON MULTIMEDIA LIMITED | 03138158 | 2465 |

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|---|---|---|
| JEBCORP TRADING LIMITED | 03237557 | 5530 |
| QUEENSBURY STRUCTURES LIMITED | 03127568 | 2875 |
| REPOWER MINING INTERNATIONAL LIMITED | 03060001 | 2852 |
| SOVEREIGN TV LIMITED | 02904115 | 5245 |
| V.E.C. (PURFLEET) LIMITED | 03113156 | 7484 |
| DEVIZES WINDOWS LTD | 03168157 | 4525 |
| BANDOL ESTATES LIMITED | 00524059 | 7499 |
| HYOSUNG U.K. LIMITED | 01360706 | 5170 |
| FARRINGTON GOLF CENTRE LIMITED | 02449412 | 9272 |
| ACAS-AIR CONDITIONING AND ALLIED SERVICES LIMITED | 01125886 | 4534 |
| AZUNA LIMITED | 01759004 | 1930 |
| EMPLOYERS REINSURANCE INTERNATIONAL LIMITED | 01994425 | 6603 |
| SUPREME COMPUTER SERVICES LIMITED | 01622446 | 7260 |
| HONEYBOURNE HIDE & SKIN CO. LTD. | 02601679 | 1910 |
| STYLE REPLACEMENT WINDOWS LIMITED | SC124645 | 4544 |
| HEXAR LIMITED | 02870777 | 3220 |
| KARMA (UK) LIMITED | 02869985 | 7484 |
| CRIATON LIMITED | 02030481 | 9305 |
| EXECUTRAIN UK LIMITED | 02784281 | 7220 |
| F.S.CLAPTON LIMITED | 00811848 | 6024 |
| MALYEAR LIMITED | 02428905 | 5511 |
| RURAL FORUM SCOTLAND | SC118792 | 8532 |
| SHEERBONNET MARKETING LIMITED | 02667291 | 9272 |
| FASHIONHOUSE DYNAMICS LIMITED | 02781310 | 5142 |
| G.B. CIRCUITS LIMITED | 02399922 | 3210 |
| IPW - INSULATIONS LIMITED | 02106804 | 2852 |
| REALCOURT LIMITED | 03160148 | 9305 |
| ROTORUA LIMITED | 02697341 | 7484 |
| VETRA INTERNATIONAL LIMITED | 01953527 | 2222 |
| WILUNDY LIMITED | 03055876 | 7260 |
| CATALYST CREATIVE GROUP PLC | 03185581 | 7415 |
| SHREDDIT PLC | 03163108 | 7484 |
| ALMA (LONDON) LIMITED | 00359722 | 5142 |
| WIG AND PEN CLUB LIMITED | 00511366 | 5540 |
| BRIDGEMOOR LIMITED | 02607332 | 7484 |
| GILMER LIMITED | 00368914 | 4525 |
| I. S AND G (IPSWICH) LIMITED | 02344434 | 7499 |
| SANDTON TUBES LIMITED | 02427141 | 2710 |
| CHJS LIMITED | 02051700 | 7440 |
| G. AND R. CADWALLADER LIMITED | 02712440 | 6024 |
| ISC MEDIA SYSTEMS LIMITED | 02971875 | 7220 |
| OFFICEHASTE PROJECTS LIMITED | 02787503 | 2222 |
| THE CENTRAL CLINIC LIMITED | 03064756 | 8514 |
| ANIMATION FESTIVAL LIMITED(THE) | 01828641 | 2513 |
| BUSINESS LINK (HULL & EAST RIDING) LIMITED | 03087241 | 7484 |
| CARDCOUNT LIMITED | 03139272 | 2222 |
| CHARLES HARBAGE ENGINEERING LIMITED | 03075504 | 2924 |
| HANNING PLASTICS LIMITED | 03102926 | 2524 |
| SHINHO ELECTRONICS & COMMUNICATIONS (UK) COMPANY LIMITED | SC169829 | 7260 |
| WOODGRANGE METAL STAMPING CO.LIMITED | 00357325 | 2872 |
| SHERELLE INTERNATIONAL LIMITED | 01081511 | 5144 |
| WENDOGABLE LIMITED | 01470499 | 4521 |
| CONTESSA FURNISHINGS (LONDON) LIMITED | 01046224 | 5143 |
| DES TECHNOLOGY EUROPE LTD | 02330271 | 7220 |
| GLEAVE CONSTRUCTION LIMITED | 02359411 | 4521 |
| HADLINGTON DESIGN LIMITED | 02102925 | 3663 |
| MERTON TRAINING CONSORTIUM LIMITED | 01754068 | 8022 |
| NEWCOM ELECTRICAL WHOLESALE LIMITED | 01589011 | 5143 |
| THRESHOLD SERVICES LIMITED | 02258723 | 9305 |
| TRESTE PLANT HIRE LIMITED | 02631345 | 2875 |
| TERRE LIMITED | 02761831 | 7440 |
| CLEARWATER OILS LIMITED | 00265248 | 2320 |
| COMPUTERS 1252 LIMITED | 02412075 | 5164 |
| CONTINENTAL SATELLITE TV LIMITED | 02954437 | 9220 |
| FOOD & BEVERAGE COMPANY (OXFORD) LTD | 02368040 | 5530 |
| H.S. SIMONS & CO. ENGINEERS LIMITED | 00429475 | 2922 |
| STUDENT LINE LIMITED | 02856548 | 6420 |
| L P SECURITY PLC | 02747218 | 9305 |
| MALLARDHAVEN S.T. LIMITED | 03090184 | 7484 |
| MASTERSOFT SOLUTIONS LIMITED | 03043384 | 7220 |
| PRETTY UGLY POTTERY LIMITED | 02364212 | 3663 |
| WOKING CONSERVATIVE CLUB LIMITED(THE) | 00737525 | 7484 |

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| D C O BAR & GRILL LIMITED | 03145518 | 5530 |
| LEONELLA BLOUSES LIMITED | 00587832 | 5142 |
| AMACOM INTERNATIONAL LIMITED | 02280201 | 7440 |
| BISHOPSGATE STEELS LIMITED | 01917549 | 5170 |
| DAI-ICHI EUROPE LIMITED | 01735839 | 6523 |
| ISISFINE LIMITED | 02215381 | 7415 |
| WEST END MOTORS (SWANSEA) LIMITED | 01531562 | 5010 |
| B.B. LEASING LIMITED | 00645428 | 5010 |
| BAKERS OF WOOLWICH LIMITED | 00648070 | 5247 |
| BEKEN & SON LIMITED | 00997191 | 5231 |
| BELMONT ASPHALT COMPANY LIMITED | 01769675 | 4521 |
| FINELINE PRINTING LIMITED | 01385447 | 2222 |
| GEERE & CO. LIMITED | 00519870 | 4525 |
| GENERAL COUNCIL AND REGISTER OF OSTEOPATHS LIMITED THE | 00316704 | 9112 |
| GPC TENNOC LIMITED | 01384355 | 7499 |
| NORTHERN BLACKMORE LIMITED | 00586328 | 6601 |
| BERREY & UNDERWOOD LIMITED | 00282537 | 1754 |
| FIRMCOOL LIMITED | 02536148 | 4544 |
| J.J.M. TRANSPORT LIMITED | 02615687 | 6024 |
| ROUGHAM TANKS LIMITED | 02531661 | 4521 |
| SENTINEL SPRINKLERS LIMITED | 01297961 | 2852 |
| AXXYSS GROUP LIMITED | 02560949 | 7415 |
| PEVIJURE LIMITED | 00784370 | 7499 |
| PROPRINTER (NOTTINGHAM) LTD. | 02854083 | 2222 |
| THE FRACTAL PARTNERSHIP LIMITED | 02683013 | 7220 |
| TSAF LIMITED | 02866612 | 2222 |
| ANDERSON DOMESTIC APPLIANCES LTD. | 02743995 | 9305 |
| EUROPIA LIMITED | 02850740 | 9305 |
| FINGERSAFE (U.K.) LIMITED | 02890977 | 5170 |
| FIRST NEWS LIMITED | 02733724 | 5226 |
| LIBRASTAT LIMITED | 02931688 | 5164 |
| MMI GROUP LIMITED | SC153341 | 7220 |
| NU-GEN (BAKERY SYSTEMS) LIMITED | 02562995 | 3663 |
| SPRING MOBILE TRAINING LIMITED | 02992081 | 7499 |
| WELLSTOR PAINTS AND LACQUERS LIMITED | 00874592 | 3614 |
| ACTINET COMPUTERS LIMITED | 02969332 | 7220 |
| ALBION REAL ESTATE CORPORATION LIMITED | 00673085 | 7011 |
| MARK J. SHAW INTERNATIONAL TRANSPORT LIMITED | 02766932 | 6024 |
| VANCOUVER STUDIOS LIMITED | 03148559 | 2513 |
| BASCOURT LIMITED | 03196624 | 5248 |
| GEMINI SHOPFITTERS LIMITED | 03217298 | 4534 |
| VISCOUNT TRAVEL LIMITED | 00783511 | 6330 |
| RAINBOW OFFICE GROUP LIMITED | 01891721 | 5170 |
| ASSORTED ALLOYS LIMITED | 02555514 | 5157 |
| HESKETH INTERNATIONAL FUND MANAGEMENT LTD. | 02028191 | 6523 |
| MIDDLESBROUGH MACHINE COMPANY LIMITED | 00920781 | 2852 |
| JABMAN COMPANY LIMITED | 00825310 | 7484 |
| LONDON & INTERNATIONAL MERCANTILE LIMITED | 01521077 | 6512 |
| MEDIELITE PLC | 01892338 | 5170 |
| MAINLINE ACCESSORIES LIMITED | 02732834 | 5170 |
| VOCOM GROUP PLC | 02713453 | 7220 |
| WHITE MOUNTAIN FOODS LIMITED | 02805854 | 5111 |
| ANCESTORS LIMITED | 02865669 | 3663 |
| ATTICBASIC LTD | 02893719 | 3663 |
| CAPITAL & COUNTY CONSTRUCTION LIMITED | 02228893 | 4521 |
| HARTLEY AND BEALES CONSTRUCTION LIMITED | 02955118 | 7011 |
| ISMAN LIMITED | 02857261 | 9305 |
| PBH SERVICECO LIMITED | 02962965 | 7415 |
| PERFORMANCE MANAGEMENT SERVICES (MILTON KEYNES) LIMITED | 02417901 | 7414 |
| BLENHEIM TECHNICAL ASSOCIATES LIMITED | 02484210 | 7220 |
| CAMBRIDGE PASSENGER CRUISERS LIMITED | 02988709 | 9272 |
| LANGLEY ARCHITECTURAL LIMITED | 03110700 | 9305 |
| PEDUS LIMITED | 03039517 | 7499 |
| ELECMOD LIMITED | 03373087 | 5165 |
| NEW WILLCOX LIMITED | 01119016 | 5170 |
| SOLINIA LIMITED | 00473357 | 7499 |
| BELLSHILL ENGINE SALES LIMITED | 01297253 | 2911 |
| LEEDS MOTOR FACTORS CO. (L.M.F.) LIMITED | 01170822 | 5030 |
| MEETING SYSTEMS INTERNATIONAL LIMITED | 02200298 | 7484 |
| R.H.HIGGS & SONS LIMITED | 00635160 | 5248 |
| RALSTON PURINA INTERNATIONAL (UK) LIMITED | 02202230 | 5139 |
| ROLIMPEX (U.K.) LIMITED | 02416531 | 5139 |

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| WESTERN MANAGEMENT LIMITED | 01896298 | 7011 |
| BRACKENHURST INVESTMENTS LIMITED | 01025491 | 7484 |
| CENTURY HOUSE INFORMATION LIMITED | 02112126 | 2213 |
| SUNQUEST TRAVEL LIMITED | 01084674 | 6330 |
| XT WINDOWS & DOORS MANUFACTURING LIMITED | 01466239 | 2524 |
| O'SULLIVAN & MASON (HEATING) LIMITED | 02662121 | 4533 |
| ALFRED BLACKMORE HEALTHCARE LIMITED | 02906996 | 6603 |
| FREEWHEEL (LONDON) LIMITED | 02970221 | 5248 |
| M & M CONTRACTORS LIMITED | 02948243 | 4521 |
| PAGEMATCH LIMITED | 02980490 | 4521 |
| PANAQUA HOLDINGS PLC | 02939665 | 3330 |
| THE APPLIANCE WAREHOUSE LIMITED | 02991197 | 5245 |
| WHITEHEAD AND LARN LIMITED | 01122092 | 4533 |
| YEARCO LIMITED | 02956932 | 9111 |
| AMTOOL HIRE COMPANY LIMITED | 01226661 | 4550 |
| ARMSTRONG DESIGNS LIMITED | 03095029 | 2852 |
| CHOICE OFFICE SYSTEMS LIMITED | 02811786 | 9305 |
| HEXAWARE TECHNOLOGIES U. K. LIMITED | 03109256 | 7220 |
| KPE (REALISATIONS) LIMITED | 02792287 | 2940 |
| LASTOR LIMITED | SC136488 | 7414 |
| MULTI SERVICES LIMITED | 02606661 | 2513 |
| SUPREME D LIMITED | 03056407 | 9305 |
| WILEYS LTD. | SC162296 | 5211 |
| TOPICLAND (LEICESTER) LIMITED | 03263971 | 6420 |
| DILLWYN CONSTRUCTION LIMITED | 01172209 | 4521 |
| ZENITH PLANT HIRE LIMITED | 00864381 | 7499 |
| A-LINE (LONDON) LIMITED | 02448455 | 4521 |
| FREEMAN ELECTRICAL WHITECHAPEL LIMITED | 01407211 | 4531 |
| OVERSEAS TEXTILE TRADERS LIMITED | 02517403 | 5141 |
| R.J.CHAPPELL LIMITED | 00548717 | 5226 |
| RIGHTBOLD LIMITED | 02005281 | 7484 |
| C. & M. GROUNDWORK LIMITED | 01168666 | 4521 |
| JENSON TUNGSTEN LIMITED | 02415006 | 2875 |
| LAMBTON CAR SALES LIMITED | 02134510 | 5050 |
| MASTERZONE LIMITED | 02808691 | 2211 |
| SKY ROOFING LIMITED | 02493565 | 4522 |
| CYNGOR FFILM CYMRU/THE WALES FILM COUNCIL | 02832819 | 9231 |
| HENVIS CAR SERVICES LIMITED | 00957619 | 6022 |
| HONEYCREST LIMITED | 03023207 | 5530 |
| INTERNATIONAL SALES AND MARKETING LTD. | 02968011 | 5151 |
| NORTH KENSINGTON CITY CHALLENGE COMPANY LIMITED | 02758061 | 7512 |
| R.S. CARDBOARD BOXES LIMITED | 01585561 | 2121 |
| SK SECURITIES EUROPE LIMITED | 02977850 | 6523 |
| THE POST-GRADUATE NUTRITION AND DIETETIC CENTRE | SC132108 | 2513 |
| WATERSHIP DOWN COOLERS LIMITED | 02927025 | 5170 |
| A.S.I. INTERNATIONAL (UK) LIMITED | 03101770 | 7220 |
| DATACARE RESOURCES U.K. LIMITED | 03024901 | 9305 |
| HORIZON METAL FINISHING LIMITED | 01501759 | 2741 |
| MANSYS LIMITED | SC163880 | 7260 |
| PRIORY PARK INSURANCE SERVICES LIMITED | 01039983 | 6601 |
| THAMES DAIRY FOODS LIMITED | 02940423 | 0121 |
| THE BELL MEDIA GROUP PLC | 02378650 | 9231 |
| DIBBEN CONSTRUCTION LIMITED | 01288004 | 4521 |
| HUGH PUSHMAN ASSOCIATES LIMITED | 01253529 | 6420 |
| ISK BIOSCIENCES LIMITED | 01713173 | 2420 |
| STANHOPE ADMINISTRATION LIMITED | 02134806 | 7484 |
| ARNPRIDE LIMITED | 02312469 | 7011 |
| BURGESS AND GALER LIMITED | 00476371 | 5246 |
| CONCEPT GLASS LIMITED | 01597822 | 2611 |
| ESSEX MARINA LIMITED | 01409028 | 9305 |
| FLAMETEX FILLINGS LIMITED | 00609342 | 7499 |
| GARDESS STAIR MANUFACTURING CO. LIMITED | 01589805 | 9305 |
| H. STONES & SONS LIMITED | 00751319 | 6024 |
| HOUSEMASTERS (WEST LONDON) LIMITED | 00976648 | 5147 |
| NATCO (UK) LIMITED | 02390472 | 7499 |
| TONG YANG SECURITIES EUROPE LIMITED | 02598001 | 6523 |
| ADEPT COMPUTER SYSTEMS LIMITED | 01436690 | 5170 |
| ASHFARE LIMITED | 00515170 | 5143 |
| CAM FURNITURE LIMITED | 02673600 | 3611 |
| EDUCATIONAL PROJECT RESOURCES LIMITED | 01377714 | 8021 |
| RIAZ KNITWEAR (MANCHESTER) LIMITED | 02502644 | 1822 |
| SEATECH LIMITED | 00922233 | 3511 |

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|---|---|---|
| TEA TRADE PROPERTIES LIMITED | 00984254 | 7020 |
| TUDOL U.K. LIMITED | 01497082 | 6340 |
| BENNETT'S TRANSPORT (SHEFFIELD) LIMITED | 01075602 | 6024 |
| MEDICAL INNOVATIONS LIMITED | 02780959 | 5146 |
| PHOENIX GRANULATORS LIMITED | 02601038 | 5157 |
| SHARHILL LIMITED | 01113426 | 7499 |
| ARENA REALISATIONS LIMITED | 02708344 | 7420 |
| BARNET INSULATION COMPANY LIMITED | 00710568 | 4532 |
| BMP LIMITED | 02757120 | 7420 |
| BOSS MAINTENANCE LIMITED | 02903703 | 4545 |
| FCS (UK) LIMITED | 02982521 | 7484 |
| MICRO-INTEGRATION CORP. PLC | 03019759 | 7220 |
| NATIONWIDE FLEET SERVICES LIMITED | 02948634 | 7110 |
| PANAQUA PROCESS LTD | 02945175 | 9305 |
| PHOENIX HYDRAULICS (UK) LIMITED | 03016507 | 5161 |
| SAIL SOFTWARE LIMITED | 02865393 | 9305 |
| STONE CO-ORDINATED CERAMICS (SOUTHERN) LIMITED | 02535441 | 2625 |
| TOPGUYS AND CECILY LIMITED | 02983034 | 5242 |
| CASTLEMILK PARTNERSHIP TEAM LIMITED | SC156574 | 9305 |
| CYBERTEC LIMITED | 02801020 | 5245 |
| DIRECT DISTRIBUTORS (NORTHERN) LIMITED | 02749604 | 5245 |
| ELECTRICAL TESTING & CONTRACTING SERVICES LIMITED | 03129365 | 4531 |
| J.SMETHURST & SON(BOLTON)LIMITED | 00514461 | 2710 |
| NAT COMPOLITE LIMITED | 03156166 | 7484 |
| NIGEL DAVIES LIMITED | 03023124 | 9305 |
| PRIZEWIN LIMITED | 03178815 | 1589 |
| STRATHALBA LIMITED | SC164904 | 5540 |
| GUILE POINT LIMITED | SC018296 | 9305 |
| K.CHELLARAM & SONS(LONDON)LIMITED | 00425052 | 5170 |
| YARMOUTH LIMITED | 00748001 | 5143 |
| PRONTO E-MECH LIMITED | 01988160 | 5156 |
| ALLIED PROFILES LIMITED | 01062530 | 5170 |
| CORTEK SERVICES LIMITED | 01564161 | 7260 |
| DAVID RUFFLE ARCHITECTS LIMITED | 01842779 | 7484 |
| GULVAL PROPERTIES LIMITED | 00597841 | 7011 |
| HYROLEC PURCHASING AND EXPORT LIMITED | 02299942 | 5170 |
| STEVEDORING SERVICES (SWANSEA) LIMITED | 02542420 | 6110 |
| ALFRED BLACKMORE & CO (SCOTLAND) LIMITED | SC095778 | 6603 |
| DENNIS FARM (HOLDINGS) LIMITED | 01578590 | 7484 |
| G. ROBERTSON (INSURANCE BROKERS) LIMITED | SC048222 | 7484 |
| GRANTS CONTRACTS (EAST) LIMITED | SC025661 | 5244 |
| IMPULSE PROMOTIONS LIMITED | 01724955 | 7499 |
| JANSENS LIMITED | 01858507 | 7499 |
| L.& G.AUTO SERVICES LIMITED | 00930611 | 5010 |
| M.B.T. TRANSPORT SERVICES LIMITED | 02435174 | 6024 |
| MALLARDHAVEN GEO LIMITED | 02316639 | 9305 |
| REVERT LIMITED | 01696332 | 7220 |
| TOKAI MARUMAN SECURITIES (EUROPE) LIMITED | 02142024 | 6523 |
| TRIDENT PRINT & DESIGN PLC | 02078343 | 2222 |
| WESSEX WOOD PRODUCTS LIMITED | 02059073 | 5170 |
| WOODPECKER REPROGRAPHICS (ESSEX) LIMITED | 02373836 | 2222 |
| CULTURAL PARTNERSHIPS LIMITED | 01786343 | 9305 |
| NATIONAL SECURITIES OF JAPAN (EUROPE) LIMITED | 02026405 | 6523 |
| PRISECTER INTERNATIONAL LIMITED | 02321249 | 7420 |
| SOCAM METERS PUBLIC LIMITED COMPANY | 02299935 | 5170 |
| FLORISLOANE LIMITED | 02633665 | 7499 |
| LETMINI LIMITED | 02360911 | 6110 |
| LINEX LIMITED | 02689540 | 9305 |
| MARINI LIMITED | 01843101 | 5242 |
| ROSENTHAL STUDIO HOUSE (LONDON) LIMITED | 01002686 | 7499 |
| WHEELBRACE LIMITED | 02796624 | 5010 |
| MOSAIC MICROSYSTEMS LIMITED | 02623251 | 7499 |
| CAMCO PROP ENGINEERING LTD | 02817671 | 9305 |
| EXPRESS MICRO LIMITED | 03117725 | 7499 |
| H.E. FRY LIMITED | 00829186 | 7499 |
| MAINSPARK LIMITED | 02848659 | 2513 |
| ORBIT SHIPPING & TRADING COMPANY LTD. | 02731919 | 6340 |
| PAX SURVEILLANCE SYSTEMS LTD. | 02975720 | 7484 |
| PHELAN SALES INTERNATIONAL LIMITED | 02790893 | 5114 |
| PRUDENTIAL MAINTENANCE LIMITED | 02831177 | 9305 |
| ANGEION EUROPE LIMITED | 03109034 | 7484 |
| BALDWIN HAULAGE LTD. | 03080612 | 6024 |

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|---|---|---|
| CASTLE MOTOR AUCTIONS LIMITED | 03048320 | 5010 |
| COAST TO COAST FISH MERCHANTS LIMITED | 03178296 | 5138 |
| DISCOUNT CARPET CO.LIMITED | 00723707 | 5244 |
| INSTANT-SHUT BOX COMPANY LIMITED | 00800752 | 2121 |
| LENCO MOTOR SPARES (HASTINGS) LIMITED | 03023714 | 5010 |
| MACKENZIE HAULAGE (IRVINE) LIMITED | SC048877 | 6024 |
| PERRY (HESTON) LIMITED | 01426635 | 5231 |
| UNIVERSAL LINE SERVICES LIMITED | 02984056 | 7484 |
| VALLEY CHINACRAFT LIMITED | 01352254 | 5246 |
| WILLIAM DAW AND SONS LIMITED | 01124043 | 4533 |
| WIND COMPUTERS LIMITED | 02994203 | 7220 |
| CLIFFORD WHATMOUGH(HOLDINGS)LIMITED | 00455429 | 7415 |
| HOWARTH TIMBER (RICHMOND) LIMITED | 00181367 | 7499 |
| SHIPBREAKING (QUEENBOROUGH) LIMITED | 00812083 | 4511 |
| SUNTORY (U.K.) LIMITED | 01764293 | 5134 |
| COMMENT CLUBS LTD | 01672703 | 5540 |
| GEORGE BANKS MANAGEMENT SERVICES LIMITED | 01253119 | 1930 |
| JACK BUSHBY (LITHO) LIMITED | 01797448 | 2222 |
| L & P RUN OFF LIMITED | 01190662 | 6601 |
| LEESAND LIMITED | 01441111 | 5141 |
| MAZARD HOTEL MANAGEMENT LIMITED | 02566851 | 7484 |
| SENTRACHEM INTERNATIONAL LIMITED | 02144406 | 7414 |
| CENTRAL RAILWAY PROJECT LIMITED | 02437699 | 7499 |
| D.M. BUILDING CONTRACTORS LIMITED | 02532272 | 4521 |
| FIRST TEMPTATION COMPUTERS LIMITED | 02555974 | 7220 |
| HOWARD'S PET SUPPLIES LIMITED | 00976193 | 5170 |
| KINGCLIP SEAFOODS LIMITED | SC108343 | 5132 |
| LEATHER FASHIONS LIMITED | 00723343 | 5141 |
| NORMA JEAN (MFG) LIMITED | 01934045 | 1822 |
| PROBITAS LIMITED | 01174564 | 4521 |
| TRAVEL TRADE CONSULTANTS LIMITED | 01476529 | 6330 |
| ALLIED BUSINESS SUPPLIES LIMITED | 02653570 | 5170 |
| CARROT (UK) LIMITED | 02596238 | 7440 |
| LITTLE LEIGHTON SOBCZYK LIMITED | 02624804 | 7440 |
| RESEARCH DEFENCE SOCIETY | 02581634 | 9112 |
| STRAEKER DESIGN AND BUILD LIMITED | 02624589 | 4521 |
| UNICOIN (NEW HOMES) PLC | 02387898 | 4521 |
| CAPITAL RADIO RESTAURANTS HOLDINGS LIMITED | 02889521 | 5530 |
| CORNISH QUALITY BACON LIMITED | 01204535 | 7499 |
| EVE VALERE LIMITED | 00460201 | 7499 |
| MINGLES MUSIC LIMITED | 01265668 | 9231 |
| RICHCLIFF (GROUP) LIMITED | 01019947 | 7484 |
| ALEXANDER MURDOCH LIMITED | SC036314 | 4521 |
| CEENET | 03058671 | 7484 |
| CHAPTER 2 BOOKS AND VIDEOS LIMITED | 02956216 | 5247 |
| COMPUTER INSTALLATIONS LIMITED | 01774706 | 7260 |
| COX, HEPBURN (FINANCIAL SERVICES) LIMITED | 02096955 | 6523 |
| D.R.A. HOLDINGS LIMITED | 02942493 | 9305 |
| GERARD WALSH & CO. LIMITED | 01707681 | 5170 |
| GLASGOW STONE SPECIALISTS LIMITED | SC102367 | 4525 |
| GLOBAL SPORTS PRODUCTIONS LIMITED | 02843712 | 9231 |
| HEALTH SOLUTIONS LIMITED | 03062998 | 8514 |
| L.W.JOHNSON PLANT (LONDON) LIMITED | 00985956 | 4550 |
| M & P HARRIS LIMITED | 02742346 | 5211 |
| MORAY ALARMS LIMITED | SC106843 | 9305 |
| SUTTON JONES MULTIMEDIA LIMITED | 03032494 | 7440 |
| TEES COUNTRY PRODUCTS LIMITED | 02932123 | 2625 |
| TERWISGA (UK) LIMITED | 02925890 | 9305 |
| TPL (1991/7) LIMITED | 02661438 | 5170 |
| TRACS SUPPLIES LIMITED | 02938540 | 5146 |
| W.F. TOOL SUPPLIERS LIMITED | 02639708 | 9305 |
| ALLIED NETWORKS SCQ LIMITED | 03141047 | 6420 |
| BUSINESS DESIGNS LIMITED | 02933942 | 4534 |
| DATA-MESSAGE LIMITED | 03008153 | 5245 |
| HALLMARK COMMUNICATIONS LIMITED | 03044711 | 6411 |
| J. & M. ROBINSON (BUILDERS) LIMITED | 01919002 | 4521 |
| JB CONSULTANCY LIMITED | 03182097 | 7499 |
| LIFESIGN DIAGNOSTIC SERVICES LIMITED | 03125715 | 8512 |
| OLIVERS MOTOR FITTINGS LIMITED | 00511125 | 5010 |
| PETERS SHIRT MAKERS (BRISTOL) LIMITED | 00338218 | 5248 |
| TECHCENTER LIMITED | 02719011 | 7450 |
| TRAINEEZE LIMITED | 03104548 | 8042 |

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|---|---|---|
| ARMOURGLASS UK LIMITED | 03192427 | 2611 |
| AWED LIMITED | 03203048 | 5250 |
| MOUNTBLAZE LIMITED | 03152646 | 7011 |
| NORTHANTS AUTO ELECTRICAL SERVICES LIMITED | 03211637 | 7484 |
| CRENDON HOLDINGS LIMITED | 01694815 | 2661 |
| DUNWILCO (527) LIMITED | 01958176 | 7499 |
| PRICEACRE LIMITED | 02483321 | 7415 |
| LEES WHITEHEAD LIMITED | 00810790 | 5131 |
| R.C.TOPHAM LIMITED | 00600100 | 0130 |
| SHAWE LIGHTING LIMITED | 00503809 | 5143 |
| CRANBOURNE TOURS LIMITED | 02314748 | 6330 |
| EUROCONTINENTAL (ADVISERS) LIMITED | 02214990 | 7484 |
| FAHR BUCHER (UK) LIMITED | 01440839 | 2924 |
| FREEDOM GRAPHICS LIMITED | 02516008 | 2222 |
| LANCASTER LEISURE PARK LIMITED | 02286508 | 7020 |
| MANCHESTER EXECUTIVE HOMES PLC | 02305382 | 7011 |
| MONK-DUBIED LIMITED | 02195096 | 2954 |
| P & AJ LIMITED | 00457943 | 4531 |
| PRINTECH PRINTING MACHINERY LIMITED | 02323455 | 5170 |
| REZNOR LIMITED | 02426941 | 2852 |
| RUGARTH PROPERTY MANAGEMENT CO. LIMITED | 00526632 | 7499 |
| SAI WESTALL TOMKINS LIMITED | 02028764 | 7440 |
| SHANNING MARKETING LIMITED | 01885985 | 5146 |
| SPALDING ELECTRICAL LINITED | 00652497 | 5245 |
| STRUCTURAL FOUNDATION SERVICES LIMITED | 02261332 | 2513 |
| SURVEY AND GENERAL MANAGEMENT CO.LIMITED | 00793176 | 7011 |
| UNITED STANDARD INSURANCE COMPANY LIMITED | 00095707 | 6603 |
| BANDUNG LIMITED | 02376307 | 9231 |
| BAYNOT PROPERTY CO.,LIMITED | 00475005 | 7011 |
| BLACKWELL SERVICES LIMITED | 00736189 | 6601 |
| BROOMCO (1500) LIMITED | 02097469 | 6523 |
| KIDORT LIMITED | 01641054 | 5170 |
| LEISURE PARK DEVELOPMENTS LIMITED | 00935113 | 5523 |
| LOUVRES LIMITED | 02443049 | 7499 |
| NORWICH PROPERTY MANAGEMENT LIMITED | 02197942 | 7032 |
| PROJECT INSIGHT CONSULTANTS LIMITED | 02643590 | 7220 |
| R.P.(CONSULTANTS)LIMITED | 00640405 | 7499 |
| SBS UK LIMITED | 02646500 | 7415 |
| CAMPBELL HELLOWELL DUNCAN LIMITED | SC105847 | 7484 |
| CENTRELINE PROPERTIES (DEVELOPMENTS) LIMITED | 01324826 | 7499 |
| GUIDEDETAIL LIMITED | 02570404 | 4533 |
| MONSAL FARMS LIMITED | 02112714 | 0122 |
| APPLEDOOR LIMITED | 00815570 | 5212 |
| HOUSE OF TRAVEL (HAVANT) LIMITED | 01015694 | 6330 |
| PARKES & SIMPSON LIMITED | 01128174 | 0123 |
| THE RESIDENCES AT ST. CATHERINE'S I PLC | 02823265 | 7011 |
| UNITED REAL ESTATE PLC | 02452730 | 7011 |
| 180-PHARMACY LIMITED | 00991119 | 7499 |
| ADELA ESTATES LIMITED | 00367919 | 7011 |
| BATES (INSURANCE) LIMITED | 00614288 | 6603 |
| DEATH BECOMES ME LIMITED | 02865917 | 9305 |
| DISYS LIMITED | 02396844 | 3320 |
| EGGLESTONS (CONTRACTORS) LIMITED | 01896635 | 4550 |
| GEM TRANSPORTATION SERVICES (ANGLIA) LIMITED | 01642804 | 6024 |
| HOVE CAMERA COMPANY LIMITED | 02863917 | 5248 |
| JARDINE ARBER AND COMPANY LIMITED | 02645776 | 7414 |
| JAS (READING) LIMITED | 02743298 | 2213 |
| MRJ GROUP LIMITED | 02862519 | 7415 |
| OVENS REALISATIONS LIMITED | 01387277 | 2921 |
| PDC INTERNATIONAL ENGINEERING LIMITED | 02870870 | 9305 |
| POOLADDY LIMITED | 01259289 | 9271 |
| SKYTRONICS SYSTEMS LTD. | 01916919 | 7220 |
| THE SUIT CTR LIMITED | 02368693 | 7499 |
| YU & ME SUPERSTORE LIMITED | 02844908 | 5212 |
| CLANDATA LIMITED | 03227438 | 7484 |
| CONCEPT GRAPHICS LIMITED | 03173805 | 7484 |
| H & C INTERNATIONAL TRANSPORT LIMITED | 03095436 | 6024 |
| MALTACTION LIMITED | 02810768 | 1822 |
| PATHWAY LABORATORY SERVICES LIMITED | 02459191 | 7484 |
| SAXON DIRECT LIMITED | 02971302 | 5170 |
| THE RESIDENCES AT JESUS COLLEGE PLC | 02823851 | 9600 |
| THE RESIDENCES AT ST. HILDA'S PLC | 02823278 | 9600 |

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| TOTEM TECHNOLOGY LIMITED | 03178557 | 7499 |
| CLI EUROPE LIMITED | 03252350 | 7499 |
| EYEWITNESS SECURITY LIMITED | 03221708 | 7484 |
| LAWGRA (NO.363) LIMITED | 03199172 | 7484 |
| BEN LINE GROUP LIMITED | SC098801 | 7499 |
| CHINEHAM FOODS LIMITED | 01496365 | 5117 |
| SANDTON STEELS LIMITED | 02165139 | 2710 |
| SCOTFRESH (1997) LIMITED | SC093594 | 1533 |
| STOREDALE PLC | 01513412 | 7499 |
| BARGAIN PROMOTIONS LIMITED | 01100865 | 5212 |
| OLD SYSTEMS PLC | 02343339 | 7220 |
| B+S MANUFACTURING EUROPE LIMITED | 02453775 | 2875 |
| BRAZIER METALS LIMITED | 01384190 | 5157 |
| DOMEFLAG LIMITED | 01851719 | 4521 |
| ASHBY LONDON LIMITED | 01705906 | 6523 |
| ATOS U.K. LIMITED | 02523014 | 5170 |
| BYTOP LIMITED | 01326207 | 7011 |
| CAMOMILE UNDERWRITING AGENCIES LIMITED | 01307485 | 6601 |
| DUNLOP ARMALINE LIMITED | 00597479 | 7499 |
| FLEETMASTER (U.K.) LIMITED | 01074469 | 5170 |
| FRIERNGROVE LIMITED | 01408168 | 7220 |
| MIRAGE TRAVEL LIMITED | 02143332 | 6330 |
| MITO EUROPE LIMITED | 02063921 | 6712 |
| ROMEDE FLOWERS LIMITED | 01599355 | 5170 |
| SITEMODE SYSTEMS LIMITED | 02511336 | 5170 |
| SOFT-SWITCH LIMITED | 02529576 | 7499 |
| STOCK (DISTILLERS) LIMITED | 00458759 | 5134 |

| COMPANY NAME | Registered Number | SIC Code |
|---|---|---|
| J. SAINSBURY PLC | IE185647 | 5211 |
| WATERFORD FOODS PLC | IE105940 | 2922 |
| P&O NEDLLOYD LIMITED | 00857789 | 6110 |
| INTERNATIONAL COMPUTERS LIMITED | NF000668 | 7220 |
| QUINNSWORTH | IE036991 | 2922 |
| JAMES CREAN PLC | IE009222 | 1598 |
| INTERNATIONAL PUBLISHING CORPORATION LIMITED | 00745584 | 2213 |
| GUINNESS IRELAND LIMITED | IE059784 | 1595 |
| NORTHERN IRELAND ELECTRICITY PLC | NI026041 | 4010 |
| IRISH DAIRY BOARD LTD | IE040615 | 2922 |
| UNITED TOURISM (HOLDINGS) LIMITED | 02837553 | 6330 |
| DSL GROUP LIMITED | 03206563 | 9305 |
| GREENCORE GROUP PLC | IE170116 | 2922 |
| WATERFORD CRYSTAL LIMITED | IE078088 | 2922 |
| IRISH PERMANENT PUBLIC LIMITED COMPANY | IE222332 | 6511 |
| GATEWAY 2000 IRELAND LTD | IE200852 | 2922 |
| L M ERICSSON HOLDINGS LTD | IE093135 | 6420 |
| BDO STOY HAYWARD SERVICES | 02789024 | 7484 |
| AROMATICS HOLDINGS LTD | IE060693 | 2922 |
| UNIDARE PLC | IE012128 | 2822 |
| PANTRY FRANCHISE IRELAND LIMITED | IE056673 | 2922 |
| NOMURA EH LIMITED | 03212661 | 7484 |
| GUARDIAN PMPA GROUP LTD | IE145359 | 6601 |
| THE MERCANTILE AND GENERAL REINSURANCE COMPANY LIMITED | SA000341 | 2922 |
| GOLDEN WEST FOODS LIMITED | 01601427 | 1589 |
| MUSEFIELD LIMITED | 01581197 | 5170 |
| COBRA SPORTS LIMITED | 01413501 | 5243 |
| MARCONI AEROSPACE UNLIMITED | 00516425 | 3320 |
| I E C HOLDINGS LIMITED | IE192635 | 2922 |
| WALSH WESTERN (HOLDINGS) LIMITED | IE106235 | 2922 |
| GLOBAL LOGISTICS LIMITED | IE189923 | 2922 |
| DEFENCE SYSTEMS LIMITED | 01540857 | 7484 |
| ULSTER WEAVERS HOME FASHIONS LIMITED | NI00R751 | 1740 |
| SHERWOOD MEDICAL INDUSTRIES OF IRELAND LTD | IE077037 | 8514 |
| SUPERMAC'S IRELAND LIMITED | IE150005 | 5530 |
| GROUP 4 SECURITAS IRELAND LIMITED | IE025701 | 7524 |
| UNITED DRUG PUBLIC LIMITED COMPANY | IE012244 | 5146 |
| MB IRELAND LIMITED | IE166341 | 3650 |
| HERDMANS LIMITED | NI00R347 | 1711 |
| WATERFORD STANLEY LIMITED | IE084827 | 2922 |
| GIX INTERNATIONAL LIMITED | 03089096 | 2862 |
| PDC ENGINEERING LIMITED | 03031482 | 4521 |
| ASCON LTD | IE017543 | 4521 |
| CARTON GROUP LTD | IE063235 | 1513 |
| GARRETT IRELAND | IE063614 | 2753 |
| BOSTON SCIENTIFIC IRELAND LTD | IE213232 | 5146 |
| BLARNEY WOOLLEN MILLS LIMITED | IE025875 | 5261 |
| CHARRINGTONS FUELS LTD | 00654265 | 5151 |
| NESTLE (IRELAND) LIMITED | IE001614 | 1584 |
| MATER PRIVATE HOSPITAL LTD | IE099197 | 8511 |
| SAEHAN MEDIA IRELAND LIMITED | IE121863 | 3230 |
| HUNTSMAN ICI EUROPE LIMITED | 01003645 | 7310 |
| SOLA ADC LENSES LIMITED | IE060388 | 3340 |
| STRATUS HOLDING AND FINANCE COMPANY LIMITED | IE137208 | 2922 |
| S. P. S. INTERNATIONAL LTD | IE018032 | 2874 |
| THE INSURANCE CORPORATION OF IRELAND LIMITED | IE143108 | 6601 |
| PINELEVEL LIMITED | 02707860 | 8531 |
| BERWIN LEIGHTON SERVICES | 02906195 | 9305 |
| FBD INSURANCE PUBLIC LIMITED COMPANY | IE025475 | 6601 |
| CBT GROUP PUBLIC LIMITED COMPANY | IE148294 | 2922 |
| M.B.C. LIMITED | 02266529 | 9220 |
| FINE DECOR LIMITED | 02380451 | 5154 |
| PETROLEUM GEO-SERVICES (UK) LIMITED | 02874539 | 1120 |
| GMX LIMITED | IE142403 | 2971 |
| DARMONT LIMITED | 02889950 | 7220 |
| TLC BEATRICE INT. (IRL) HOLDINGS LTD | IE124239 | 2922 |
| RACAL HEALTH & SAFETY LIMITED | 01379114 | 2956 |
| EXCELER HEALTHCARE SERVICES LEASING LIMITED | 02276013 | 8514 |
| JANSSEN PHARMACEUTICAL LTD | IE079963 | 2441 |
| IRELAND KOTOBUKI ELECTRONICS INDUSTRIES LIMITED | IE171517 | 2922 |
| DUBLIN PRIVATE HOSPITALS LTD | IE007606 | 8511 |

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|---|---|---|
| REMBIA (INDONESIA) LIMITED | 01654165 | 0201 |
| ASEA BROWN BOVERI LIMITED | IE011420 | 5165 |
| SCHIESSER INTERNATIONAL (IRELAND) | IE022233 | 1823 |
| DYNCORP AEROSPACE OPERATIONS (UK) LTD | 02965556 | 9305 |
| INFORMIX SOFTWARE IRELAND LTD | IE196983 | 7220 |
| TRIPLEX FOUNDRY LIMITED | 00674652 | 2751 |
| KB REALISATIONS LIMITED | 01940939 | 5242 |
| DUNGANNON MEATS | NI016970 | 1511 |
| ALPHA-NUMERIC(MAIDENHEAD)LIMITED | 00867846 | 7220 |
| HOERMANN ELECTRONICS LTD | IE084121 | 2922 |
| EAGLE STAR LIFE ASSURANCE COMPANY OF IRELAND LTD | IE058098 | 6601 |
| PROJECT MANAGEMENT HOLDINGS LTD | IE122309 | 2922 |
| QUANTUM PERIPHERAL PRODUCTS (IRELAND) LTD | IE178545 | 3002 |
| DEEPWELL INVESTMENTS LIMITED | IE015922 | 2922 |
| WESSEL INDUSTRIES HOLDINGS LTD | IE083461 | 2922 |
| BROOKS GROUP LIMITED | IE072563 | 2922 |
| THE E.I. COMPANY LIMITED | IE114252 | 2922 |
| SUNGEI BAHRU RUBBER ESTATES PLC(THE) | 00263487 | 0141 |
| TOP FLIGHT RECRUITMENT LTD. | 01367823 | 7450 |
| MUNEKATA IRELAND LIMITED | IE121242 | 3663 |
| ANTIGEN HOLDINGS LIMITED | IE151826 | 2922 |
| TIMELINE TRAVEL LIMITED | 02653355 | 6021 |
| SHELL COMPANY OF THE SUDAN,LIMITED(THE) | 00202231 | 7484 |
| DENMAN INTERNATIONAL LIMITED | NI008800 | 2922 |
| D J FREEMAN SERVICES | 02866029 | 7484 |
| STANLEY COOKERS LTD | IE188202 | 2922 |
| THE BRAEBURN GROUP LIMITED | SC077876 | 2523 |
| AMS MANAGEMENT SYSTEMS U.K. LTD. | 02406054 | 7414 |
| FUJITSU ISOTEC IRELAND LIMITED | IE139642 | 2922 |
| WALSH WESTERN INTERNATIONAL LTD | IE091837 | 6024 |
| ASHTEAD PLANT HIRE COMPANY (IRELAND) LIMITED | 02766044 | 4550 |
| GAELIC SEAFOODS (HOLDINGS) LIMITED | 02634752 | 0502 |
| FANNIN LIMITED | IE051914 | 2922 |
| SENSORMATIC ELECTRONICS CORPORATION LTD | IE214997 | 2852 |
| CABLE PRODUCTS (IRELAND) | IE118589 | 3130 |
| BKPT. CLOTHING COMPANY LIMITED | 01970026 | 5242 |
| RANDOX LABORATORIES LIMITED | NI015738 | 3320 |
| PACKARD ELECTRIC IRELAND LTD | IE041000 | 3130 |
| JELSON LIMITED | 00571641 | 4521 |
| ALDISCON INFORMATION LIMITED | IE136206 | 2922 |
| PENARTH COMPANY LTD | IE083216 | 7415 |
| PROJECT MANAGEMENT LTD | IE043789 | 7414 |
| RICHARD KEENAN & CO. LTD | IE060803 | 2922 |
| NELLCOR PURITAN BENNETT IRELAND | IE145169 | 5232 |
| B.M.D. & COMPANY LIMITED | IE037978 | 2852 |
| PURITAN-BENNETT IRELAND LIMITED | IE145170 | 2922 |
| LISK IRELAND LIMITED | IE068192 | 3210 |
| RIV-BAK REALISATIONS LIMITED | SC060517 | 5139 |
| NENA MODELS LTD | IE024840 | 5142 |
| SCOTTISH AMICABLE INTERN. ASSURANCE MANAGE. SERV | IE209958 | 2922 |
| INTERNATIONAL PUBLISHING ASSOCIATES LIMITED | 02714255 | 2956 |
| JOHN THOMPSON & SONS LIMITED | NI00R447 | 1571 |
| SIGMA COMMUNICATIONS GROUP LIMITED | IE174198 | 2922 |
| ANC RENTAL (EUROPE) | 02996258 | 7110 |
| FR RESOURCES | 02941694 | 7484 |
| RTITB SERVICES LIMITED | 02735862 | 9305 |
| THOMAS & BETTS HOLDINGS (U.K.) LIMITED | 02287881 | 2862 |
| CRAMWELL LTD | IE226388 | 2922 |
| ENSCO OFFSHORE U.K. LIMITED | 02868165 | 1110 |
| ELECTRO MECHANICAL SOLUTIONS LIMITED | NI007686 | 3663 |
| SEAN QUINN PROPERTIES LIMITED | IE120282 | 5511 |
| EARLSFORT CENTRE HOTEL PROPRIETORS LTD | IE126939 | 2922 |
| PARKLANDS CARE HOMES (YORKSHIRE) LIMITED | 02082304 | 5511 |
| CLONMEL CHEMICALS COMPANY LTD. | IE030591 | 2922 |
| CENTREX LIMITED | 02967449 | 7484 |
| ANS HOMECARE LIMITED | 02372202 | 7450 |
| MCINERNEY CONSTRUCTION LIMITED | IE024066 | 4521 |
| INTERNATIONAL TRANSLATION & PUBLISHING LTD | IE135925 | 7220 |
| ROBERT SAVAGE LTD | IE050972 | 7412 |
| M. KELLIHER & SONS (1935) LIMITED | IE008997 | 2922 |
| ADVANCE TYRE COMPANY LTD | IE016846 | 5030 |
| UNION CAMP HOLDINGS LTD | IE069619 | 7415 |

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| TIE/COMMUNICATIONS UK LIMITED | 01568445 | 3220 |
| SYDNEY INSURANCE & REINSURANCE LIMITED | IE053272 | 6601 |
| FOYLE MEATS | NI011193 | 1511 |
| JA/MONT IRELAND LIMITED | IE008693 | 2051 |
| IRISH PROGRESSIVE MANAGEMENT SERVICES LTD | IE236813 | 6601 |
| CARROLLS AQUACULTURE LIMITED | IE118389 | 5010 |
| HGW PAINTS LIMITED | IE003567 | 2430 |
| MBD NATIONAL LIMITED | 02697205 | 5170 |
| GALLAGHER BROTHERS LIMITED | IE035160 | 5138 |
| XCESS INDUSTRIAL DRIVERS LTD | IE192141 | 8041 |
| MENTEC LIMITED | IE076578 | 2922 |
| JAY BEE LTD | IE017203 | 2922 |
| THOMAS MC DONOGH & SONS LTD | IE007832 | 5113 |
| JAMES NORTH FOOTWEAR LIMITED | 02285648 | 1930 |
| BRITISH GAS TUNISIA LIMITED | 02750465 | 1110 |
| VITAL SECURITY LTD. | 03122730 | 7460 |
| CONNAUGHT ELECTRONICS LIMITED, | IE092489 | 2922 |
| KILLYBEGS SEAFOODS LTD | IE026902 | 1520 |
| KELLYS STRAND HOTEL LTD | IE023574 | 2922 |
| MICROLINK INDUSTRIES LIMITED | 02069776 | 2745 |
| VIRGIN RETAIL GROUP LIMITED | 02376810 | 5245 |
| UNIPHAR PUBLIC LIMITED COMPANY | IE224324 | 5146 |
| CHASE MANHATTAN BANK (IRELAND) PUBLIC LIMITED CO. | IE007566 | 6511 |
| MCGHAN LIMITED | IE143419 | 3310 |
| PCC REALISATIONS LIMITED | SC085002 | 4550 |
| DAVID PATTON (HOLDINGS) LTD | IE104382 | 2922 |
| ARTHUR RING & SONS LIMITED | IE025498 | 2812 |
| GOODRICH HOLDING UK LIMITED | 02425914 | 3530 |
| SUDBROOK LTD | IE156748 | 2922 |
| GATE GOURMET IRELAND LTD | IE096836 | 5552 |
| NATIONS EUROPE LIMITED | 01404562 | 6512 |
| SAVEHEAT INSULATIONS LIMITED | SC059036 | 4544 |
| OMAGH MEATS | NI025364 | 1511 |
| GALVIA HOSPITAL (HOLDINGS) PUBLIC | IE104993 | 2922 |
| ROWEAR LTD | IE073091 | 2922 |
| ALLIED FOODS LIMITED, | IE133365 | 2922 |
| THE FIN MACHINE COMPANY LIMITED | 02714045 | 2852 |
| MILLAIS INVESTMENTS LIMITED | IE251574 | 7414 |
| I.G. HALE (HOLDINGS) LIMITED | 01487903 | 4521 |
| SOUDE JEWELLERY LIMITED | 00903768 | 3622 |
| PETER CRAIG & SON LIMITED | SC116677 | 4533 |
| TORTUBE LIMITED | 01170728 | 2875 |
| MICROMOTORS GROSCHOPP IRELAND LTD | IE029594 | 3110 |
| APC LIMITED | SC153533 | 4550 |
| DONALDSON, LUFKIN & JENRETTE INTERNATIONAL | 02475089 | 6712 |
| THE FLEET STREET INN LIMITED | IE194678 | 2922 |
| INDUSTRIAL PRINT (HOLDINGS) LIMITED | IE161678 | 2922 |
| ZARNDOAH LTD | IE135804 | 2922 |
| PIERRE VICTOIRE LIMITED | SC106768 | 5530 |
| MUNRO'S TRANSPORT (ABERDEEN) LIMITED | SC023570 | 6024 |
| IRISHENCO HOLDINGS | IE078721 | 2922 |
| SNIPGROVE LIMITED | 02503330 | 9305 |
| DES KELLY CARPETS LIMITED | IE055165 | 2922 |
| KNOCKDENE GARAGES LIMITED | NI008067 | 5010 |
| QUEST INTERNATIONAL IRELAND LTD | IE055437 | 2922 |
| EQUINOX CARE | 02114430 | 8531 |
| SIMON AERIALS LIMITED | IE058299 | 2922 |
| FIRST INFORMATION GROUP PLC | 02839085 | 2213 |
| MARATHON SPORTS LTD | IE086330 | 3640 |
| W H BOOTH & CO LIMITED | 00962366 | 2751 |
| ESLUP REALISATIONS PLC | 02370816 | 3650 |
| LONTEX INDUSTRIES LIMITED | 02524736 | 2470 |
| BURMAH CASTROL (IRELAND) LIMITED | IE008142 | 2922 |
| LEWIS SILKIN SERVICES | 02820913 | 7484 |
| I.I. (REALISATIONS) LIMITED | 01133587 | 2956 |
| CLARIS MANUFACTURING LIMITED | IE142140 | 2922 |
| CLARIS IRELAND HOLDINGS LIMITED | IE121164 | 7415 |
| CUISINE DE FRANCE LIMITED | IE149525 | 2922 |
| IRISH MARKETING SURVEYS GROUP LTD | IE020372 | 7413 |
| AVOCA HANDWEAVERS SHOPS LTD | IE046106 | 2922 |
| SUNPAK & MAYFIELD FRESH PRODUCE LIMITED | IE126017 | 5131 |
| JOSEPH BRENNAN BAKERIES LIMITED | IE036555 | 2922 |

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| NMC COMPANY LTD | IE130880 | 5010 |
| ENBI (IRELAND) LIMITED | IE059676 | 2922 |
| OLD BUSHMILLS DISTILLERY COMPANY LIMITED | NI000601 | 2924 |
| WILSON HARTNELL GROUP | IE022248 | 9211 |
| CONSOLIDATED SYSTEM BUILDING PLC | 03012670 | 9305 |
| CATERING MANAGEMENT IRELAND LIMITED | IE161825 | 5552 |
| LITHOGRAPHIC UNIVERSAL LTD | IE012416 | 2922 |
| WOCO INDUSTRIAL COMPONENTS LIMITED | IE055690 | 3210 |
| MERCER LTD | IE028158 | 9111 |
| LIVERPOOL TANNING COMPANY LIMITED(THE) | 00040433 | 1910 |
| MICHAEL GUINEY LIMITED. | IE034465 | 5241 |
| POWER IMPORT AND WHOLESALE LTD | IE027172 | 5141 |
| TEACHERS ASSURANCE COMPANY LIMITED | 00314801 | 6601 |
| MCDERMOTT LABORATORIES LIMITED | IE110075 | 2441 |
| D.H BURKE & SON LTD | IE059533 | 2922 |
| LANCASTER NURSING HOME LIMITED | 02001507 | 8514 |
| ELIZABETH ALEXANDRA LIMITED | NI009795 | 1822 |
| EURHOTEL LTD | IE064624 | 2922 |
| XILINX IRELAND | IE190265 | 2852 |
| MONK COTTON GROUP LIMITED | 03014657 | 2954 |
| FULL CIRCLE BEDROOMS LIMITED | 01477845 | 5246 |
| HARTMAN IRELAND LIMITED | IE064106 | 3614 |
| ENERGY CONSERVATION SYSTEMS (N.I.) LIMITED | NI016146 | 3663 |
| COREL CORPORATION LTD | IE200857 | 2922 |
| WALSH WESTERN MANUFACTURING LIMITED | IE149163 | 2233 |
| PRESSTECH CONTROLS GROUP LIMITED | 03162385 | 3162 |
| WOLFF OLINS LIMITED | 01945130 | 7414 |
| BREWERY CHEMICAL & DAIRY ENGINEERING LIMITED | IE093074 | 2852 |
| TACONIC INTERNATIONAL LIMITED | IE050505 | 2615 |
| HOTEL KILKENNY LTD | IE103660 | 2922 |
| PLAY PRINT LTD | IE031866 | 2922 |
| RADLEY ENGINEERING LTD | IE038811 | 2852 |
| INDUSTRIAL PRINT LTD., | IE053511 | 2922 |
| FRASER GRAY CONTRACTS LIMITED | SC051343 | 4521 |
| RYAN'S INVESTMENTS LIMITED | IE020261 | 7110 |
| SIGMA WIRELESS TECHNOLOGIES LIMITED | IE178926 | 2922 |
| CHINA MERCHANTS HOLDINGS (UK) LIMITED | 02185395 | 7415 |
| ROYAL TARA CHINA HOLDINGS LTD | IE100992 | 5144 |
| OLHAUSENS LIMITED | IE008929 | 2922 |
| C.E.M. COMPUTERS LIMITED | NI014278 | 5164 |
| RENNICKS MANUFACTURING | IE047753 | 2922 |
| HAYES HYDRAULIC CASTINGS LIMITED | 03035332 | 2751 |
| HANRATTY HOLDINGS LIMITED | IE028926 | 2922 |
| TOP SECURITY LIMITED | IE119839 | 6712 |
| JMM LIMITED | SC014797 | 5010 |
| DUBLIN DRUG PUBLIC LIMITED COMPANY | IE153033 | 2922 |
| DONEDEE LIMITED | 00735521 | 5552 |
| D D U.K. LIMITED | 02072220 | 1581 |
| PARK DEVELOPMENTS (DUBLIN) LIMITED | IE027777 | 2922 |
| GRAPHIC GROUP LTD | IE163593 | 2922 |
| GEC DISTRIBUTORS (IRELAND) LIMITED | IE016132 | 5143 |
| BRAZIER LIMITED | 00997457 | 4521 |
| G. BELL & SONS LTD | NI019343 | 2922 |
| SILAVENT (HOLDINGS) LIMITED | 00596872 | 7415 |
| O'HARA'S OF FOXFORD LTD | IE072942 | 5136 |
| ZEAL HOLDINGS LIMITED | 02479376 | 3320 |
| FTP SOFTWARE LIMITED | 02417148 | 7220 |
| MEROPS (NUTRITION) LIMITED | IE057489 | 2922 |
| TOP TECH IRELAND LIMITED | IE128177 | 2922 |
| TAYLOR DYNE ELECTRICAL SYSTEMS LTD | 01921251 | 3130 |
| D. O'SULLIVAN (IRELAND) LTD | IE021721 | 2430 |
| THF CARE ESTATES LIMITED | 00674277 | 9305 |
| GRANBY LIMITED | IE018553 | 2922 |
| THE IMPERIAL HOTEL (CORK) LTD | IE045339 | 2922 |
| WEIR & SONS (DUBLIN), LTD | IE007597 | 2922 |
| WILLIAM REID ENGINEERING LIMITED | SC032387 | 4525 |
| THORMAC ENGINEERING LTD., | IE065043 | 5161 |
| EDCREST LIMITED | 02194791 | 6024 |
| CHESHAMBEL LIMITED | 00896276 | 5511 |
| LARNE HARBOUR LIMITED | NI00R472 | 6322 |
| BASCROWN LIMITED | 01842619 | 5143 |
| WYCOMBE MARSH HOLDINGS LIMITED | 00790849 | 5010 |

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| AVOCA HANDWEAVERS LIMITED | IE046720 | 1722 |
| ARGEE C STORES LIMITED | SC096852 | 5212 |
| FERRYCARRIG CASTLE HOTEL LTD | IE047132 | 2922 |
| JACOBS/PEGASUS ENGINEERING LTD | IE081894 | 2852 |
| HUNT BROS. (OLDBURY) LIMITED | 00161473 | 2751 |
| FARM & COUNTRY LIMITED | 02531444 | 5166 |
| WATERLINK (UK) LIMITED | 02387229 | 2811 |
| STONE DEVELOPMENTS LTD | IE021700 | 2922 |
| CHECKPOINT SYSTEMS (UK) LIMITED | 02118737 | 5118 |
| EQUANT NETWORK SERVICES LIMITED | 02635954 | 7484 |
| ZCCM (UK) LTD | 01740003 | 5170 |
| SMYTHS TOYS LTD | IE119138 | 3650 |
| THE M.P. DOYLE GROUP LTD | IE146886 | 2922 |
| BLUE - FLITE LIMITED | IE053953 | 6412 |
| 3COM-SONIX LIMITED | 02711561 | 3220 |
| PRESSTECH CONTROLS LIMITED | 02752505 | 3320 |
| WESTERTEX (LOUGHBOROUGH) LIMITED | 01330960 | 9999 |
| IRISH MERCHANTS LIMITED | IE058083 | 2922 |
| MICA & MICANITE (IRELAND) LTD | IE023898 | 2922 |
| O'MALLEY CONSTRUCTION COMPANY LIMITED | IE034570 | 4521 |
| A G B SCIENTIFIC LIMITED | IE036744 | 3320 |
| BOWEN CONSTRUCTION LIMITED | IE026240 | 4521 |
| AIG EUROPE (IRELAND) LTD | IE053654 | 6603 |
| INTRAPORT PLC | 01210500 | 5142 |
| MALLOW FOODS LIMITED | IE111999 | 2922 |
| WARNER-LAMBERT IRELAND LTD | IE016287 | 1584 |
| CORK COMMUNICATIONS LIMITED | IE077758 | 9220 |
| MAYSTEEL CME TEORANTA | IE193272 | 2922 |
| SCHAFFNER LTD | IE073913 | 3162 |
| DUGGAN STEEL (IRL) LIMITED | IE053853 | 2922 |
| GOLDCROP HOLDINGS LIMITED | IE108112 | 2922 |
| MURRAY TIMBER PRODUCTS LIMITED | IE056033 | 2922 |
| INSIGHT SOFTWARE LIMITED | IE067792 | 7220 |
| GREEN SUNRISE HOLDINGS LTD | IE241574 | 7415 |
| SERVICE INDUSTRIES LIMITED | 01680983 | 7220 |
| BS AND B SAFETY SYSTEMS LIMITED | IE048049 | 2922 |
| F S W COATINGS LIMITED | IE062617 | 2922 |
| TEGREL LIMITED | 01897468 | 3162 |
| SOUTH EAST REGIONAL TOURISM AUTHORITY LTD | IE021207 | 2922 |
| FRAMEMAKER PRODUCTS LIMITED | 01029006 | 2051 |
| O'SHEA'S ELECTRICAL LTD | IE081666 | 2922 |
| VENTILUX LTD | IE115670 | 3150 |
| METALLGESELLSCHAFT LIMITED | 00972941 | 6523 |
| SHANNON TRANSPORT & WAREHOUSING COMPANY LTD | IE043409 | 6024 |
| FOXRUN INVESTMENTS LIMITED | 02784356 | 9305 |
| FRIENDS FIRST BROKER SERVICES LIMITED | IE234194 | 6720 |
| CSC COMPUTER SCIENCES IRELAND LIMITED | IE213308 | 2922 |
| JOHN TINSLEY LIMITED | 00910824 | 2931 |
| CASCADE DESIGNS LIMITED | IE101688 | 2922 |
| CELTIC SEA FOODS LIMITED | IE103202 | 1520 |
| FORTE TRAVELODGE IRELAND LIMITED | IE160774 | 2922 |
| JAMESWAY PRINT FINISHERS LIMITED | 02727024 | 2223 |
| MAXIM CONSTRUCTION LIMITED | 01664654 | 4521 |
| REDISCOVERED ORIGINALS BY HARRY BROWN LIMITED | 02259960 | 5242 |
| CROSSGUNS BAKERY LTD | IE065729 | 2922 |
| QUALITY CERAMICS (ARKLOW) LIMITED | IE127353 | 2622 |
| SHERLOCK BROTHERS LIMITED | IE069137 | 2922 |
| STR-GRESHAM BUSINESS FORMS LIMITED | 01599705 | 2123 |
| CAMPBELL IRISH FOODS LIMITED | IE098846 | 1533 |
| BEAVER DISTRIBUTION LIMITED | IE017540 | 2922 |
| ALERT PACKAGING LTD | IE061242 | 2522 |
| NATWORTH LTD., | IE124890 | 2922 |
| COMMONWEALTH GOLD PLC | 03075468 | 1450 |
| BALLYMORE SECURITIES LTD | IE152387 | 4521 |
| WATFORD CIVIC THEATRE TRUST LIMITED(THE) | 00834380 | 9231 |
| GRESHAM LION TECHNOLOGY LIMITED | 02732999 | 3320 |
| TOPPS UK LIMITED | 02673753 | 2222 |
| GRESHAM LION TECHNOLOGY GROUP LIMITED | 02917664 | 3320 |
| CENTRE REINSURANCE DUBLIN | IE235549 | 6601 |
| THE MOWLEM CONSTRUCTION COMPANY (EAST AFRICA) LIMITED | 00775010 | 4521 |
| ALLIED METROPOLE HOTEL LTD | IE006127 | 2922 |
| W. DEACON & SONS LTD | IE061779 | 2922 |

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| ERIN HORTICULTURE LIMITED | IE069455 | 2922 |
| THE DUNRAVEN ARMS HOTEL LTD | IE076479 | 2922 |
| TIMONEY HOLDINGS LTD | IE071823 | 2922 |
| G. W. BIGGS & COMPANY LIMITED | IE007481 | 2922 |
| HONEYCLOVER (FRESHFORD) LIMITED | IE170009 | 2922 |
| SEAFIELD TECHNICAL TEXTILES LTD | IE179450 | 2922 |
| WARTSILA DIESEL SERVICE LIMITED | 02771434 | 5030 |
| WORKTOWN LIMITED | 01376231 | 7011 |
| LAKE HOLDINGS LIMITED | IE036890 | 2922 |
| DATAPRODUCTS TECHNOLOGIES LTD | IE197049 | 2922 |
| BRADFIELD HOUSE LIMITED | 01345080 | 8021 |
| ELY & SIDNEY LIMITED | 01571323 | 5141 |
| DAVID PATTON LIMITED | IE012827 | 2922 |
| GRANT ENGINEERING LIMITED | IE066680 | 2822 |
| O'SHEA'S LIMITED | IE121126 | 2812 |
| THE DUBLIN WELL WOMAN CENTRE LTD | IE059290 | 2922 |
| T.T.B.(FABRICATIONS)LIMITED | 00869964 | 2821 |
| THORNHOPE SHIPPING COMPANY,LIMITED(THE) | 00383629 | 6110 |
| CALMORE LIMITED | IE119230 | 5142 |
| COOPERS LIMITED | IE023199 | 5154 |
| LADYFIELD INVESTMENTS LIMITED | IE158835 | 7415 |
| PLAYPOLE (UK) LIMITED | 02660844 | 5263 |
| TEDCASTLES OIL PRODUCTS LIMITED | IE018083 | 5151 |
| FIRS NURSING HOME LIMITED(THE) | 01861637 | 7011 |
| AYLWYN INVESTMENTS LIMITED | IE077500 | 2922 |
| HOLMES PLACE CITY LIMITED | 02037402 | 9272 |
| T. J. O'MAHONY & SONS LIMITED | IE078139 | 5113 |
| ATLANTIC PROJECTS COMPANY LTD | IE203538 | 2922 |
| T.J. O'MAHONY & SONS (HOLDINGS) LTD | IE016999 | 5113 |
| THE LADY VERDIN TRUST LIMITED | 02750298 | 8531 |
| THOS. KING & SONS (BUILDERS) LIMITED | 00468023 | 4521 |
| A. F. KNIGHTS ELECTRICAL & MECHANICAL LTD. | 00847142 | 4531 |
| GREEN AND BINGHAM LIMITED | 00465240 | 2875 |
| CETREK LIMITED | 00993547 | 3210 |
| MICHAEL LYNCH LIMITED | IE051056 | 4521 |
| IASC MARA TEORANTA | IE189008 | 1520 |
| MY KINDA BAILE LTD | IE129411 | 5540 |
| REVLON PROFESSIONAL LIMITED | IE016944 | 5233 |
| THE NATIONAL CONCERT HALL | IE081897 | 2922 |
| EXEL WALSH WESTERN LIMITED | IE248292 | 2922 |
| HAMLET INTERNATIONAL PLC | 00915135 | 5142 |
| THE HAMMOND LANE METAL COMPANY LIMITED | IE009123 | 2922 |
| CUPID MANUFACTURING LIMITED | 03221108 | 1822 |
| THE VOLUNTEER CENTRE - THE CENTRE FOR VOLUNTEERING COMMUNITY A | SC166042 | 7484 |
| A. C. NIELSEN OF IRELAND LTD | IE018335 | 7413 |
| CORBY ROCK EGGS LTD | IE040791 | 5133 |
| LOGSTRUP LIMITED | IE058370 | 3120 |
| RED SAIL EXPORTS LTD | IE055797 | 1520 |
| EUROPLAST TEORANTA | IE038582 | 2524 |
| GUINNESS WORLD RECORDS LIMITED | 00541295 | 2211 |
| CYCLOCARD LIMITED | 01963328 | 5540 |
| FIDELITY LITHOGRAPHIC COMPANY LIMITED | 00743897 | 2222 |
| SENATOR PLASTICS LIMITED | 02232844 | 2524 |
| GLENPATRICK SPRING WATER COMPANY LIMITED | IE023529 | 2922 |
| PATRICK MONAHAN (DROGHEDA) LTD | IE034144 | 1010 |
| MEDNET | 02678416 | 6603 |
| JOHNSONS SHOES COMPANY | 00983688 | 5243 |
| THE HUDDLESTON CENTRE IN HACKNEY | 02856946 | 9305 |
| MOTCHMAN & WATKINS (THEATRE) LIMITED | 01388106 | 9234 |
| MUNSTER CARPETS LIMITED | IE167339 | 1751 |
| TRAVELODGE LIMITED | IE119673 | 2922 |
| O'CONNORS GROUP HOLDINGS LIMITED | IE141628 | 7415 |
| TOTEM GROUP LIMITED | 02851382 | 7484 |
| COMPUTICKET LIMITED | 02789954 | 9305 |
| BAYER LIMITED | IE016996 | 5155 |
| CARGLASS LIMITED | IE059088 | 5020 |
| MORAYSHIRE TRACTORS LIMITED | SC031365 | 5166 |
| PURE PINE LIMITED | 02411778 | 2051 |
| THE VOICE GROUP LIMITED | 02857975 | 2215 |
| MILLER GROUP LTD | IE196325 | 2922 |
| CABLETRON SYSTEMS (DISTRIBUTION) LTD | IE215318 | 2922 |
| APPLIED SYSTEMS ENGINEERING (UK) LIMITED | 02131020 | 7220 |

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| E. P. MOONEY & COMPANY LIMITED | IE035674 | 5010 |
| G. C. MCKEOWN & CO. LIMITED | IE053993 | 7220 |
| MEDENTECH (HOLDINGS) LIMITED | IE169124 | 2922 |
| JP KENNY EXPLORATION & PRODUCTION LIMITED | 02379247 | 1110 |
| IRISH HELICOPTERS LIMITED | IE027315 | 2922 |
| IROPHARM LIMITED | IE091451 | 2922 |
| JOHN BARNES LIMITED | 02862287 | 1721 |
| WOODFAB PACKAGING LIMITED | IE047073 | 2040 |
| MICHAEL BLACK P.L.C. | SC016534 | 5143 |
| CEDAR BUILDING CO. LTD | IE048786 | 2922 |
| MODERN PLANT LTD | IE016255 | 3210 |
| WATERS MUNSTER GLASS LIMITED | IE002159 | 5246 |
| CLANCOURT GROUP HOLDINGS LIMITED | IE063041 | 7020 |
| JAMES BOYLAN & SON LIMITED | IE011438 | 2922 |
| M.S.C. PACKAGING LIMITED | 01140494 | 2121 |
| MERIDIAN VAT PROCESSING (N. AMERICA) LTD | IE197184 | 2922 |
| FREEFOAM MANUFACTURING LIMITED | IE126587 | 2922 |
| RYDES LIMITED | 01002783 | 5050 |
| DUGGAL BROS. LIMITED | 01539550 | 5142 |
| ELLICKSON ENGINEERING LTD | IE029897 | 4531 |
| CHESTER CITY FOOTBALL CLUB LIMITED | 02998020 | 9261 |
| DIVINESTATE LIMITED | 02004655 | 5143 |
| JACKETS (CATERERS) LIMITED | 01457447 | 5530 |
| PREUSSAG FIRE PROTECTION IRELAND LIMITED | IE024538 | 7525 |
| THE SAST CORPORATION LIMITED | 01492451 | 7220 |
| TABLESIDE SALES & MARKETING LIMITED | 02730943 | 5170 |
| NED O'SHEA & SONS LTD | IE029847 | 4521 |
| TRALEE WATERWORLD PLC LTD | IE195901 | 2922 |
| KERNAN TIMBER PRODUCTS LIMITED | NI015881 | 2030 |
| BDC TECHNICAL SERVICES LIMITED | 02475813 | 9305 |
| CAPCO LIMITED | IE028979 | 5153 |
| SPECIAL ANALYSIS AND SIMULATION TECHNOLOGY LIMITED | 01824834 | 7220 |
| HAROLD HOLDINGS LTD | IE020581 | 2922 |
| DUNCAN MACNEILL & COMPANY LIMITED | 00502552 | 7484 |
| NOYEKS LIMITED | IE092817 | 5113 |
| ROBERT J. GOFF & CO. PLC | IE007138 | 5111 |
| STEVENAGE YOUTH TRAINING SCHEME LIMITED | 01731533 | 9305 |
| TONY LEVOI MOTORS LIMITED | 01060111 | 5010 |
| BOWFIELD HOTEL AND COUNTRY CLUB LTD. | SC061730 | 5540 |
| BLARNEY CASTLE KNITWEAR LTD | IE062166 | 2922 |
| CLAYTON LOVE DISTRIBUTION LIMITED | IE084503 | 2922 |
| DFDS TRANSPORT LIMITED | IE072301 | 2922 |
| BRITISH ATHLETIC FEDERATION LIMITED | 02583877 | 9261 |
| THE SYNDICATE GROUP LIMITED | 02759709 | 9302 |
| AK GROUP LIMITED | 03049662 | 5170 |
| F. X. BUCKLEY LTD | IE017473 | 2922 |
| P&O SWIRE CONTAINERS LIMITED | 00971548 | 6110 |
| MITCHAM MANUFACTURING LIMITED | 01235870 | 3230 |
| ICI IRELAND LIMITED | IE021021 | 5155 |
| SUN MICROSYSTEMS IRELAND LIMITED | IE200289 | 2922 |
| INDUSTRIAL DETERGENTS LTD | IE058963 | 2922 |
| CAMBR LIMITED | 02251877 | 5170 |
| DIALOG INFORMATION SERVICES LIMITED | 01849601 | 7240 |
| C.A.B. MOTOR CO. MONAHAN ROAD LTD. | IE127597 | 5010 |
| FANNIN HEALTH CARE LIMITED | IE083973 | 7512 |
| JAMES P. RYAN & SONS LIMITED | IE024537 | 2922 |
| SIGMA WIRELESS COMMUNICATIONS LIMITED | IE174542 | 2922 |
| EWBANK PREECE ENGINEERING CONSULTANTS DUBLIN LTD | IE053280 | 2852 |
| J.C. MINI COACHES LIMITED | 02289671 | 6021 |
| EWBANK PREECE O HEOCHA LIMITED | IE154037 | 7420 |
| SHEAFLAND LTD | IE131580 | 2922 |
| COLWOOD HOUSE MEDICAL PUBLICATIONS (U.K.) LIMITED | 02213846 | 7484 |
| CHARLES WHITE (OFFICE SUPPLIES) LIMITED | 02749459 | 5164 |
| CAMFIL (IRL) LIMITED | IE086697 | 2922 |
| HOLMES PLACE (OXFORD STREET) LIMITED | 03033901 | 9261 |
| ROSTEL HOLDINGS LIMITED | 02287301 | 5119 |
| DYWM LIMITED | 03051009 | 7420 |
| PENTICA SYSTEMS LIMITED | 01462509 | 3002 |
| DEVCON LTD | IE022317 | 2922 |
| F.A. BARKER CLEANING SERVICES LIMITED | 02903922 | 9305 |
| MERIDIAN VAT PROCESSING (INTERNATIONAL) LTD | IE197186 | 2922 |
| ASHLING MICROSYSTEMS LIMITED | IE091731 | 2922 |

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| SMITH & MCLAURIN LIMITED | IE089734 | 2125 |
| S AND N FOODS LIMITED | 02346446 | 5530 |
| CYRONN LTD | 02948287 | 3663 |
| PLANET INTERNET (UK) LIMITED | 03070222 | 7220 |
| CHANDLER & DUNN LIMITED | 00538910 | 0113 |
| FRANKLIN PHARMACEUTICALS LIMITED | IE109330 | 3310 |
| ROSE HOLDINGS LTD | IE218101 | 1584 |
| ICL PATHWAY LIMITED | 03011561 | 7220 |
| GOO JOO CO LIMITED | 03080595 | 5530 |
| SLS WEST LTD | 01131136 | 2222 |
| WESTWOOD TOOLS LIMITED | 02577831 | 2940 |
| INNIL DOITEAIN TEO LTD | IE094144 | 2922 |
| LYRIC THEATRE HAMMERSMITH LIMITED(THE) | 01443809 | 9231 |
| TUBE ROLLERS LIMITED | IE046969 | 2722 |
| TURNER ACCESS LIMITED | SC045574 | 4550 |
| TRACTAMOTORS LTD | IE018753 | 2922 |
| LATCHFORD & SONS LTD | IE002790 | 2922 |
| RADLAKE LIMITED | 02714549 | 9261 |
| SILVER KING ENTERPRISES LIMITED | IE100215 | 7415 |
| TECHNICAL AIR SERVICES LIMITED | SC092015 | 4533 |
| DAWN FRESH (HOLDINGS) LTD | IE164641 | 7415 |
| C. CLIFFORD & SONS LTD. | IE012308 | 2922 |
| SMURFIT FINANCE LTD | IE065808 | 6521 |
| OCEAN FARM LIMITED | IE106914 | 5138 |
| RMS COMMUNICATIONS SYSTEMS LIMITED | 02739772 | 6420 |
| ENGELHARD METALS LIMITED | 01657318 | 9305 |
| AGFA-GEVAERT LTD | IE015007 | 5170 |
| CLYDE SURVEYS LIMITED | 01551221 | 7420 |
| EVER READY (IRELAND) LIMITED | IE008879 | 5154 |
| SHERIDAN MOTOR GROUP LIMITED | IE009843 | 5010 |
| BROIN PRINT LTD | IE205344 | 2922 |
| HUGH MCNULTY (WHOLESALE) LIMITED | IE138015 | 5131 |
| LITEPAC LIMITED | IE055385 | 7482 |
| UNIVERSITY CONCERT HALL LTD | IE206202 | 2922 |
| GEORGE KEMP STROUD AND COMPANY LIMITED | 00191909 | 4521 |
| AMICON IRELAND LTD | IE061442 | 3310 |
| BIC (IRELAND) LTD | IE037033 | 2922 |
| C & F QUADRANT LIMITED | IE055051 | 2822 |
| ECI-EUROPEAN CHEMICAL INDUSTRIES LTD | IE068403 | 2922 |
| EUROLOGIC SYSTEMS LIMITED | IE133648 | 2922 |
| HENLEY FORKLIFT IRELAND LTD | IE039589 | 5114 |
| JOHN MC CARTHY MOTORS LTD | IE047880 | 2922 |
| KITALE LTD | IE088972 | 5010 |
| LYNX GOLF (SCOTLAND) LIMITED | SC098273 | 9305 |
| OKI SYSTEMS (IRELAND) LIMITED | IE118922 | 7250 |
| MCCORMACK DENTAL LTD | IE040416 | 5232 |
| THE GRIFFINS SOCIETY | 02892836 | 8532 |
| GRAND SLAM (SPORTS AND LEISUREWEAR) LIMITED | 01355023 | 5142 |
| WESTMINSTER SCAFFOLDING GROUP PLC | 01998781 | 4525 |
| DENTON HOLME WORKING MEN'S CONSERVATIVE CLUB COMPANY LIMITED | 00536321 | 5540 |
| FALKIRK TAVERNS LIMITED | SC049468 | 5511 |
| THE ANASTASIA SOCIETY | 02610559 | 9305 |
| CORCORAN CHEMICALS LTD | IE031575 | 5155 |
| FARMHAND LTD | IE019844 | 2922 |
| MCCANN-ERICKSON LIMITED | IE172829 | 7440 |
| SWANPOOL LIMITED | IE164589 | 2922 |
| ALL-TECHNOLOGY (IRELAND) LTD | IE082823 | 2922 |
| MONAGHAN BOTTLERS LTD | IE073705 | 2922 |
| NAF NAF (BOUTIQUES) LIMITED | 02766841 | 5242 |
| ACCRINGTON PRODUCTS AND ENGINEERING CONTRACT SERVICES LIMITED | 03026591 | 2971 |
| VITAL PLANT SERVICES LTD | 03122782 | 4550 |
| ARMOR GROUP LIMITED | 01269266 | 9305 |
| MACLENNANS TRANSPORT LIMITED | SC067772 | 6024 |
| B.R.B. AND D. ELECTRICAL ENGINEERING LIMITED | 01462699 | 3110 |
| BARRS COURT HAMPERS LIMITED | 02511882 | 5139 |
| GARTONBRIDGE LIMITED | 00816147 | 9305 |
| BYEDALE LIMITED | 02684296 | 1822 |
| DINETTE LIMITED | 00583548 | 3614 |
| WHITTLE BROTHERS (CURRIERS) LIMITED | 00245334 | 1910 |
| HARRODS(BUENOS AIRES)LIMITED | 00131101 | 9302 |
| BESTPLATE (METAL FINISHING) LIMITED | 02425847 | 2875 |
| FREETIME GROUP UK LIMITED | 01711322 | 5170 |

| | | |
|---|---|---|
| ASSOCIATED PLASTICS OF IRELAND LTD | IE083041 | 2922 |
| NEW IMAGE PHOTOGRAPHICS LIMITED | 02933389 | 7481 |
| SCREEN SCENE LIMITED | IE108780 | 2232 |
| SUE RYDER REMEMBRANCE COMPANYLIMITED | 00889743 | 5212 |
| RICHARD NASH & COMPANY, LIMITED | IE007376 | 2922 |
| H.C.S. (BUILDERS) LTD. | 02713422 | 4521 |
| D.S.S. LTD | IE178028 | 2922 |
| SMITHFIELD BARS LIMITED | 02842896 | 5530 |
| VIKING COMPONENTS IRELAND LTD | IE245203 | 2922 |
| PG PROPERTIES (CHURSTON) LIMITED | 00976102 | 5010 |
| ELLERN MEDE NURSING HOME | 02004458 | 8511 |
| J. J. RUDELL & CO. LIMITED | 01259624 | 5248 |
| THOMSON OVERSEAS SERVICES LIMITED | 00616199 | 7484 |
| W. H. LUNG TRADING LIMITED | 02321830 | 9305 |
| ECF HOLDINGS LIMITED | 02575815 | 6523 |
| ABBEYFIELD WANSTEAD & WOODFORD SOCIETY LIMITED(THE) | 00677592 | 8532 |
| MEGATRONICS SERVICES LIMITED | 02872309 | 7484 |
| WHITEHEAD & PARTNERS LIMITED | 02009447 | 6523 |
| BOUGHTON INTERNATIONAL LIMITED | 00756576 | 9305 |
| PRESSFORD LIMITED | 01930067 | 3663 |
| THE IRISH STOCK EXCHANGE LTD | IE233947 | 2922 |
| TOM MURPHY HOLDINGS LIMITED | IE117368 | 7415 |
| DUNVEGAN NURSING HOME LIMITED | SC097214 | 9305 |
| HARRODS (UK) PLC | 01889348 | 7415 |
| PANTHEON HOLDINGS LIMITED | 02228512 | 6523 |
| ALEXANDER & ALEXANDER (IRELAND) LIMITED | IE010020 | 2922 |
| BARCLAY CHEMICALS MANUFACTURING LTD | IE111664 | 2922 |
| DUDLEY BOWER MAINTENANCE (INC. A M L) LTD | 02556013 | 4531 |
| PFM LIMITED | 01408669 | 6523 |
| RUSSIA LIFE MANAGEMENT LIMITED | 02700379 | 7484 |
| WORDSTAR INTERNATIONAL IRELAND | IE086334 | 7220 |
| T.R. SHELLFISH LIMITED | SC138621 | 5132 |
| AGE CONCERN TEESSIDE LIMITED | 02152353 | 8532 |
| JOHN HEATH (IRELAND) LTD | IE233296 | 3612 |
| LISSELAN FARMS LTD | IE163561 | 2922 |
| TRADEWINDS MERCHANDISING COMPANY LIMITED(THE) | 01595185 | 5141 |
| UTC (U K) LIMITED | 00211846 | 5147 |
| CIMTEL LIMITED | 01864727 | 7220 |
| SOUTH EAST ARTS BOARD | 02676777 | 8532 |
| THE DUBLIN PLYWOOD & VENEER COMPANY LIMITED | IE107578 | 5113 |
| OXFORD DIOCESAN COUNCIL FOR SOCIAL WORK INCORPORATED | 01636098 | 8511 |
| UTOPIA TECHNOLOGY PARTNERS EUROPE LIMITED | 02759724 | 7220 |
| SOIB U.K. LIMITED | 02877516 | 9305 |
| BNP CAPITAL FINANCE LTD | IE105444 | 6521 |
| H.E. INFORMATION SYSTEMS LIMITED | 02920388 | 7220 |
| GREY-SIMMONDS LIMITED | 00306403 | 5144 |
| HENRY BATH & SON LIMITED | 00162301 | 6312 |
| REDDITCH YOUNG MEN'S CHRISTIAN ASSOCIATION LIMITED | 01944516 | 7020 |
| AMALGAMATED HARDWARE LIMITED | IE039851 | 5154 |
| ASHDOWN (LEADENHALL) PLC | 02459155 | 5530 |
| BRETT BROTHERS LIMITED | IE125161 | 2922 |
| FAX INTERNATIONAL (EUROPE) LTD. | 02950386 | 6420 |
| MERTON HOUSE HOLIDAY HOTEL LIMITED | 01402197 | 9305 |
| THE NORTH WEST REGIONAL TOURISM AUTHORITY | IE021213 | 7514 |
| ESSENTIAL PICTURES LIMITED | 02521757 | 9211 |
| FOSS ELECTRIC (IRELAND) LIMITED | IE027879 | 3310 |
| HGR GROUP LIMITED | 01092449 | 7415 |
| INTERNATIONAL BIOCHEMICALS LIMITED | IE051535 | 2922 |
| PITMAN - MOORE IRELAND LIMITED | IE122770 | 5146 |
| RHONE-POULENC IRELAND LIMITED | IE090736 | 5155 |
| SELLOTAPE (IRELAND) LTD | IE045335 | 2922 |
| CLARE ISLAND SEAFARM LTD | IE109902 | 2922 |
| INTERVOYAGES (G.B.) LTD | 02837134 | 6330 |
| GTE INTERNETWORKING UK LIMITED | 01811223 | 7220 |
| BATES IRELAND ADVERTISING GROUP LIMITED | IE062282 | 2922 |
| BUSINESS LINK LONDON SOUTH LIMITED | 03023505 | 7484 |
| STONE EPPS JOINERY LIMITED | 02885721 | 4542 |
| WEST MIDLANDS CHILDRENS THEATRE (TOURING) LIMITED | 01882970 | 9231 |
| QUALITY EXAMINATION & DEVELOPMENT SERVICES (EUROPE) LIMITED | 02251043 | 7484 |
| TOWNGATE GROUP PLC | 02744473 | 5170 |
| KENTZ MANAGEMENT LTD | IE220387 | 2852 |
| CENTRE REINSURANCE INTERNATIONAL COMPANY | IE177675 | 6601 |

## Appendix D – Sample Financial Statements: Non-Bankrupt Company

During the modelling process, 2,500 financial statements of companies were examined in detail. Recall that for each company, 54 financial and cash flow ratios were carried out before submitting them as inputs to neural networks. This analysis was conducted for each company irrespective of whether the company is already bankrupt or active. The following is a sample of the financial statements examined as part of the modelling process. The following financial statements relate to J. Sainsbury Plc and their accounts were used as part of the training sets.

# J SAINSBURY PLC

| | | | |
|---|---|---|---|
| **R/O Address :** | Stamford House<br>Stamford Street<br>Blackfriars<br>London SE1 9LL | **Registered No :** | 00185647 |
| | | **Type of company :** | Public, Quoted |
| | | **Date of incorporation :** | 10/11/1922 |
| | | **Accounting Ref.Date :** | 3/28 |
| **R/O Phone :** | 0171 - 921 6000 | **Accounts Type :** | Group |
| **R/O Post Code :** | 0171 - 921 6000 | **Company Status :** | Live |
| **Latest Turnover :** | 16,433mil GBP | **Number of Holdings :** | 0 |
| **Latest No of Employees :** | 109245 | **Number of Subsid. :** | 40 |

| | | |
|---|---|---|
| **Activities :** | The retail distribution of food and home improvement and garden products. | |
| **1992 SIC UK codes :** | **Primary Code :** | 5211 - "Retail sale in non-specialised stores with food, beverages or tobacco predominating" |
| | **Secondary Code(s) :** | 5211 |
| **1981 SIC UK codes :** | **Primary Code :** | 6410 - Food retailing |
| | **Secondary Code(s) :** | 64100, 64800, 65400 |
| **Peer Group :** | 5211 - "Retail sale in non-specialised stores with food, beverages or tobacco predominating" ( VL : Very Large Companie | |

| **PROFILE** | **31/03/1999**<br>13 months<br>mil GBP | **28/02/1998**<br>12 months<br>mil GBP | **28/02/1997**<br>11 months<br>mil GBP | **31/03/1996**<br>12 months<br>mil GBP | **31/03/1995**<br>12 months<br>mil GBP | **31/03/1994**<br>12 months<br>mil GBP | **31/03/1993**<br>12 months<br>mil GBP | **31/03/1992**<br>12 months<br>mil GBP | **31/03/1991**<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **Turnover** | 16,433 | 14,500 | 13,395 | 12,627 | 11,357 | 10,583 | 9,685 | 8,695 | 8,200 |
| **Profit (Loss) before Taxation** | 888 | 719 | 609 | 712 | 809 | 369 | 733 | 628 | 518 |
| **Net Tangible Assets (Liab.)** | 5,501 | 5,123 | 4,482 | 4,235 | 3,996 | 3,708 | 3,759 | 3,236 | 2,420 |
| **Shareholder Funds** | 4,644 | 4,112 | 3,671 | 3,534 | 3,289 | 3,040 | 3,029 | 2,640 | 1,819 |
| **Profit Margin (%)** | 5.40 | 4.96 | 4.55 | 5.64 | 7.12 | 3.49 | 7.57 | 7.22 | 6.32 |
| **Return on Shareholder Funds (%)** | 17.65 | 17.49 | 18.10 | 20.15 | 24.60 | 12.14 | 24.20 | 23.78 | 28.48 |
| **Return on Capital Employed (%)** | 14.90 | 14.03 | 14.82 | 16.81 | 20.25 | 9.95 | 19.50 | 19.40 | 21.41 |
| **Liquidity Ratio** | 0.61 | 0.52 | 0.18 | 0.17 | 0.20 | 0.21 | 0.23 | 0.33 | 0.18 |
| **Gearing (%)** | 32.77 | 35.19 | 47.70 | 42.73 | 28.46 | 31.84 | 27.01 | 31.99 | 51.04 |
| **Number of Employees** | 109,245 | 107,226 | 165,992 | 154,661 | 131,298 | 124,841 | 120,119 | 112,784 | 108,987 |

| **PROFIT & LOSS ACCOUNT** | **31/03/1999**<br>13 months<br>mil GBP | **28/02/1998**<br>12 months<br>mil GBP | **28/02/1997**<br>11 months<br>mil GBP | **31/03/1996**<br>12 months<br>mil GBP | **31/03/1995**<br>12 months<br>mil GBP | **31/03/1994**<br>12 months<br>mil GBP | **31/03/1993**<br>12 months<br>mil GBP | **31/03/1992**<br>12 months<br>mil GBP | **31/03/1991**<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **Turnover** | 16,433 | 14,500 | 13,395 | 12,627 | 11,357 | 10,583 | 9,685 | 8,695 | 8,200 |
| **UK Turnover** | 14,463 | 12,803 | 11,838 | 11,198 | | | | | |
| **Overseas Turnover** | 1,970 | 1,697 | 1,557 | 1,429 | | | | | |
| **Cost of Sales** | -15,116 | -13,289 | -12,413 | -11,521 | -10,241 | | | | |
| **Total Expenses** | | | | | | | | | |
| **Gross Profit** | 1,317 | 1,211 | 982 | 1,106 | 1,116 | | | | |
| **Depreciation** | -388 | -345 | -299 | -278 | -228 | -207 | | | |
| **Other Expenses** | -93 | -76 | 12 | -72 | -50 | | | | |
| **Operating Profit** | 836 | 790 | 695 | 756 | 838 | | | | |
| **Other Income** | 60 | 42 | 37 | 24 | 7 | | | | |
| **Exceptional Items** | 107 | -9 | -29 | | | | | | |
| **Profit (Loss) before Interest** | 1,003 | 823 | 703 | 780 | 845 | 432 | 756 | 731 | 553 |
| **Interest Paid** | -115 | -104 | -94 | -68 | -36 | -63 | -23 | -103 | -35 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Profit (Loss) before Tax** | 888 | 719 | 609 | 712 | 809 | 369 | 733 | 628 | 518 |
| **Taxation** | -292 | -236 | -208 | -234 | -270 | -227 | -229 | -184 | -163 |
| **Profit (Loss) after Tax** | 596 | 483 | 401 | 478 | 539 | 142 | 504 | 444 | 355 |
| **Extraordinary Items** | -1 | -4 | 10 | -3 | -1 | -1 | -5 | 0 | 2 |
| **Minority Interests** | 2 | 4 | 2 | | | | | | |
| **Profit (Loss) for Period** | 598 | 486 | 399 | 488 | 536 | 141 | 503 | 439 | 355 |
| **Dividends** | -294 | -264 | -226 | -222 | -212 | -190 | -178 | -153 | -115 |
| **Retained Profit(Loss)** | 304 | 222 | 173 | 266 | 324 | -49 | 325 | 284 | 240 |
| **Discontinued Operations** | | | | | | | | | |
| **Audit Fee** | 1 | 1 | 1 | 1 | 1 | | | 0 | 0 |
| **Non-Audit Fee** | | | | | | | | | |
| **Amortisation of Goodwill** | | | | | | | | | |
| **Remuneration** | 1,919 | 1,667 | 1,544 | 1,405 | 1,184 | 1,188 | 938 | 849 | 748 |
| **Directors' Remuneration** | 3 | 6 | 5 | 4 | 4 | | 3 | 3 | |
| **Highest Paid Director** | 1 | 1 | 1 | | | | | 0 | |
| **Number of Employees** | 109,245 | 107,226 | 165,992 | 154,661 | 131,298 | 124,841 | 120,119 | 112,784 | 108,987 |

| BALANCE SHEET | 31/03/1999<br>13 months<br>mil GBP | 28/02/1998<br>12 months<br>mil GBP | 28/02/1997<br>11 months<br>mil GBP | 31/03/1996<br>12 months<br>mil GBP | 31/03/1995<br>12 months<br>mil GBP | 31/03/1994<br>12 months<br>mil GBP | 31/03/1993<br>12 months<br>mil GBP | 31/03/1992<br>12 months<br>mil GBP | 31/03/1991<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **Fixed Assets** | | | | | | | | | |
| **Tangible Assets** | 6,409 | 6,133 | 5,893 | 5,458 | 4,852 | 4,641 | 4,448 | 3,809 | 3,214 |
| **Land & Building** | 5,001 | 4,800 | 4,578 | 4,244 | | | | | |
| **Fixtures & Fittings** | 0 | 0 | 0 | 0 | | | | | |
| **Plant & Vehicles** | 0 | 0 | 0 | 0 | | | | | |
| **Other Fixed Assets** | | | | | | | | | |
| **Intangible Assets** | | | | | | | | | |
| **Investments** | 41 | 151 | 148 | 117 | 98 | 18 | 31 | 27 | 19 |
| **Fixed Assets** | 6,450 | 6,284 | 6,041 | 5,575 | 4,950 | 4,659 | 4,479 | 3,836 | 3,233 |
| **Current Assets** | | | | | | | | | |
| **Stock & W.I.P.** | 843 | 743 | 744 | 761 | 509 | 460 | 448 | 386 | 360 |
| **Stock** | 843 | 743 | 744 | 761 | | | | | |
| **W.I.P.** | 0 | 0 | 0 | 0 | | | | | |
| **Trade Debtors** | 54 | 50 | 73 | 52 | 31 | 113 | 44 | 32 | 115 |
| **Bank & Deposits** | 725 | 1,854 | 241 | 209 | 199 | 171 | 144 | 173 | 110 |
| **Other Current Assets** | 1,978 | 193 | 187 | 157 | 143 | 87 | 168 | 274 | 30 |
| **Group Loans (asset)** | | | | | | | | | |
| **Directors Loans (asset)** | | | | | | | | | |
| **Other Debtors** | 195 | 179 | 180 | 152 | | | | | |
| **Investm. & Other Cur. Assets** | 1,783 | 14 | 7 | 5 | | | | | |
| **Current Assets** | 3,600 | 2,840 | 1,245 | 1,179 | 882 | 831 | 804 | 868 | 616 |
| **Current Liabilities** | | | | | | | | | |
| **Trade Creditors** | -1,084 | -902 | -896 | -816 | -726 | -1,090 | -1,050 | -899 | -843 |
| **Short Term Loans & Overdrafts** | -665 | -436 | -940 | -809 | -229 | -300 | -88 | -249 | -328 |
| **Bank Overdrafts** | -293 | -268 | -580 | -581 | | | | | |
| **Group Loans (short t.)** | | | | | | | | | |
| **Director Loans (short t.)** | | | | | | | | | |
| **Hire Purch. & Leas. (short t.)** | -4 | -6 | -8 | -8 | | | | | |
| **Hire Purchase (short t.)** | | | | | | | | | |
| **Leasing (short t.)** | -4 | -6 | -8 | -8 | | | | | |
| **Other Short Term Loans** | -368 | -162 | -352 | -220 | | | | | |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Total Other Current Liabilities** | -2,800 | -2,663 | -968 | -894 | -881 | -392 | -386 | -319 | -257 |
| **Corporation Tax** | -185 | -239 | -187 | -216 | | | | | |
| **Dividends** | -217 | -193 | -162 | -160 | | | | | |
| **Accruals & Def. Inc. (sh. t.)** | -187 | -171 | -132 | -152 | | | | | |
| **Social Securities & V.A.T.** | -89 | -64 | -55 | -47 | | | | | |
| **Other Current Liabilities** | -2,122 | -1,996 | -432 | -319 | | | | | |
| **Current Liabilities** | -4,549 | -4,001 | -2,804 | -2,519 | -1,836 | -1,782 | -1,524 | -1,468 | -1,429 |
| **Net Current Assets (Liab.)** | -949 | -1,161 | -1,559 | -1,340 | -954 | -951 | -720 | -600 | -813 |
| **Net Tangible Assets (Liab.)** | 5,501 | 5,123 | 4,482 | 4,235 | 3,996 | 3,708 | 3,759 | 3,236 | 2,420 |
| **Working Capital** | -187 | -109 | -79 | -3 | -186 | -517 | -558 | -480 | -368 |
| **Total Assets** | 10,050 | 9,124 | 7,286 | 6,754 | 5,832 | 5,490 | 5,283 | 4,704 | 3,849 |
| **Total Assets less Cur. Liab.** | 5,501 | 5,123 | 4,482 | 4,235 | 3,996 | 3,708 | 3,759 | 3,236 | 2,420 |
| **Long Term Liabilities** | | | | | | | | | |
| **Long Term Debt** | -781 | -925 | -737 | -617 | -584 | -520 | -624 | -508 | -321 |
| **Group Loans (long t.)** | | | | | | | | | |
| **Director Loans (long t.)** | | | | | | | | | |
| **Hire Purch. Leas. (long t.)** | -128 | -113 | -107 | -101 | | | | | |
| **Hire Purchase (long t.)** | | | | | | | | | |
| **Leasing (long t.)** | -128 | -113 | -107 | -101 | | | | | |
| **Other Long Term Loans** | -653 | -812 | -630 | -516 | | | | | |
| **Total Other Long Term Liab.** | -31 | -48 | -69 | -84 | -102 | -131 | -89 | -71 | -67 |
| **Accruals & Def. Inc. (l. t.)** | 0 | 0 | 0 | 0 | | | | | |
| **Other Long Term Liab.** | -23 | -24 | -14 | -19 | | | | | |
| **Provisions for Other Liab.** | -8 | -24 | -55 | -65 | | | | | |
| **Deferred Tax** | | | | | | | | | |
| **Other Provisions** | -8 | -24 | -55 | -65 | | | | | |
| **Balance Sheet Minorities** | -45 | -38 | -5 | | -21 | -17 | -17 | -16 | -210 |
| **Long Term Liabilities** | -857 | -1,011 | -811 | -701 | -707 | -668 | -730 | -595 | -598 |
| **Total Assets less Liabilities** | 4,644 | 4,112 | 3,671 | 3,534 | 3,289 | 3,040 | 3,029 | 2,641 | 1,822 |
| **Shareholders Funds** | | | | | | | | | |
| **Issued Capital** | 480 | 476 | 460 | 458 | 452 | 448 | 444 | 439 | 382 |
| **Total Reserves** | 4,164 | 3,636 | 3,211 | 3,076 | 2,837 | 2,592 | 2,585 | 2,201 | 1,437 |
| **Share Premium Account** | 1,359 | 1,295 | 1,097 | 1,074 | | | | | |
| **Revaluation Reserves** | 38 | 38 | 33 | 43 | | | | | |
| **Profit (Loss) Account** | 2,767 | 2,303 | 2,081 | 1,959 | 1,798 | | | | |
| **Other Reserves** | 0 | 0 | 0 | 0 | 1,039 | | | | |
| **Shareholders Funds** | 4,644 | 4,112 | 3,671 | 3,534 | 3,289 | 3,040 | 3,029 | 2,640 | 1,819 |

| CASH FLOW STATEMENT | 31/03/1999<br>13 months<br>mil GBP | 28/02/1998<br>12 months<br>mil GBP | 28/02/1997<br>11 months<br>mil GBP | 31/03/1996<br>12 months<br>mil GBP | 31/03/1995<br>12 months<br>mil GBP | 31/03/1994<br>12 months<br>mil GBP | 31/03/1993<br>12 months<br>mil GBP | 31/03/1992<br>12 months<br>mil GBP | 31/03/1991<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **Net Cash In(Out)flow Operat. Activ.** | 1,325 | 1,149 | 1,085 | 1,012 | | | | | |
| **Net Cash In(Out)flow Ret. on Invest.** | -83 | -69 | -88 | -274 | | | | | |
| **Taxation** | -287 | -177 | -206 | -271 | | | | | |
| **Net Cash Out(In)flow Investing Activ.** | | | -988 | | | | | | |
| **Capital Expenditure & Financ. Invest.** | -698 | -583 | -723 | | | | | | |
| **Acquisition & Disposal** | 346 | 51 | -101 | | | | | | |
| **Equity Dividends Paid** | -249 | -221 | | | | | | | |
| **Management of Liquid Resources** | 3 | | -214 | | | | | | |
| **Net Cash Out(In)flow from Financing** | 211 | -252 | 396 | 167 | | | | | |
| **Increase(Decrease) Cash & Equiv.** | 568 | -102 | 149 | -354 | | | | | |

| FINANCIAL RATIOS | 31/03/1999 | 28/02/1998 | 28/02/1997 | 31/03/1996 | 31/03/1995 | 31/03/1994 | 31/03/1993 | 31/03/1992 | 31/03/1991 |
|---|---|---|---|---|---|---|---|---|---|
| **Current Ratio** | 0.79 | 0.71 | 0.44 | 0.47 | 0.48 | 0.47 | 0.53 | 0.59 | 0.43 |
| **Liquidity Ratio** | 0.61 | 0.52 | 0.18 | 0.17. | 0.20 | 0.21 | 0.23 | 0.33 | 0.18 |
| **Shareholders Liquidity Ratio** | 5.42 | 4.07 | 4.53 | 5.04 | 4.65 | 4.55 | 4.15 | 4.43 | 3.03 |
| **Solvency Ratio (%)** | 46.21 | 45.07 | 50.38 | 52.32 | 56.40 | 55.37 | 57.33 | 56.13 | 47.27 |
| **Asset Cover** | 12.87 | 9.86 | 9.89 | 10.95 | 9.99 | 10.56 | 8.47 | 9.25 | 11.96 |
| **Gearing (%)** | 32.77 | 35.19 | 47.70 | 42.73 | 28.46 | 31.84 | 27.01 | 31.99 | 51.04 |
| **Shareholders Funds per Empl. (Unit)** | 42,510 | 38,349 | 22,116 | 22,850 | 25,050 | 24,351 | 25,217 | 23,416 | 16,696 |
| **Working Capital per Employee (Unit)** | -1,712 | -1,017 | -476 | -19 | -1,417 | -4,141 | -4,645 | -4,258 | -3,377 |
| **Total Assets per Employee (Unit)** | 91,995 | 85,091 | 43,894 | 43,670 | 44,418 | 43,976 | 43,981 | 41,716 | 35,321 |

4

| PROFITABILITY RATIOS | 31/03/1999 | 28/02/1998 | 28/02/1997 | 31/03/1996 | 31/03/1995 | 31/03/1994 | 31/03/1993 | 31/03/1992 | 31/03/1991 |
|---|---|---|---|---|---|---|---|---|---|
| **Profit Margin (%)** | 5.40 | 4.96 | 4.55 | 5.64 | 7.12 | 3.49 | 7.57 | 7.22 | 6.32 |
| **Return on Shareholder Funds (%)** | 17.65 | 17.49 | 18.10 | 20.15 | 24.60 | 12.14 | 24.20 | 23.78 | 28.48 |
| **Return on Capital Employed (%)** | 14.90 | 14.03 | 14.82 | 16.81 | 20.25 | 9.95 | 19.50 | 19.40 | 21.41 |
| **Return on Total Assets (%)** | 8.84 | 7.88 | 8.36 | 10.54 | 13.87 | 6.72 | 13.87 | 13.35 | 13.46 |
| **Interest Cover** | 8.72 | 7.91 | 7.48 | 11.47 | 23.47 | 6.86 | 32.87 | 7.04 | 15.56 |
| **Stock Turnover** | 17.99 | 19.52 | 19.64 | 16.59 | 22.31 | 23.01 | 21.62 | 22.50 | 22.73 |
| **Debtors Turnover** | 280.91 | 290.00 | 200.17 | 242.83 | 366.35 | 93.65 | 220.11 | 264.30 | 71.25 |
| **Debtor Collection (days)** | 1.11 | 1.26 | 2.17 | 1.50 | 1.00 | 3.90 | 1.66 | 1.38 | 5.12 |
| **Creditors Payment (days)** | 24.08 | 22.71 | 24.42 | 23.59 | 23.33 | 37.59 | 39.57 | 37.76 | 37.56 |
| **Net Assets Turnover** | 2.76 | 2.83 | 3.26 | 2.98 | 2.84 | 2.85 | 2.58 | 2.69 | 3.39 |
| **Fixed Assets Turnover** | 2.35 | 2.31 | 2.42 | 2.26 | 2.29 | 2.27 | 2.16 | 2.27 | 2.54 |
| **Salaries/Turnover (%)** | 11.68 | 11.50 | 11.53 | 11.13 | 10.43 | 11.23 | 9.69 | 9.77 | 9.13 |
| **Turnover per Employee (Unit)** | 138,852 | 135,228 | 88,033 | 81,643 | 86,498 | 84,772 | 80,628 | 77,099 | 75,243 |
| **Average Remun. per Year (Unit)** | 16,215 | 15,547 | 10,147 | 9,084 | 9,018 | 9,516 | 7,809 | 7,530 | 6,867 |
| **Profit per Employee (Unit)** | 7,503 | 6,705 | 4,002 | 4,604 | 6,162 | 2,956 | 6,102 | 5,568 | 4,755 |

Credit Score & Rating

| | | |
|---|---|---|
| **Current QuiScore** | (Year ending 03 04 1999) | 57 Normal |
| **Previous Period's QuiScore** | (Year ending 28 02 1998) | 58 Normal |
| **QuiRating (£)** | | 100000 |

The calculations are based on accounts for relevant periods.
The QuiScore and QuiRating have been devised by Qui Credit assesment Ltd.
They must be interpreted and used in the light of the information provided by Qui Credit Assesment Ltd.

| | 31/03/1999<br>13 months<br>mil GBP | 28/02/1998<br>12 months<br>mil GBP | 28/02/1997<br>11 months<br>mil GBP | 31/03/1996<br>12 months<br>mil GBP | 31/03/1995<br>12 months<br>mil GBP | 31/03/1994<br>12 months<br>mil GBP | 31/03/1993<br>12 months<br>mil GBP | 31/03/1992<br>12 months<br>mil GBP | 31/03/1991<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **Turnover** | 16,433 | 14,500 | 13,395 | 12,627 | 11,357 | 10,583 | 9,685 | 8,695 | 8,200 |
| **Profit (Loss) before Taxation** | 888 | 719 | 609 | 712 | 809 | 369 | 733 | 628 | 518 |
| **Net Tangible Assets (Liab.)** | 5,501 | 5,123 | 4,482 | 4,235 | 3,996 | 3,708 | 3,759 | 3,236 | 2,420 |
| **Shareholder Funds** | 4,644 | 4,112 | 3,671 | 3,534 | 3,289 | 3,040 | 3,029 | 2,640 | 1,819 |

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| HISTORICAL QUISCORE & RATING | 31/03/1999<br>13 months<br>mil GBP | 28/02/1998<br>12 months<br>mil GBP | 28/02/1997<br>11 months<br>mil GBP | 31/03/1996<br>12 months<br>mil GBP | 31/03/1995<br>12 months<br>mil GBP | 31/03/1994<br>12 months<br>mil GBP | 31/03/1993<br>12 months<br>mil GBP | 31/03/1992<br>12 months<br>mil GBP | 31/03/1991<br>12 months<br>mil GBP |
|---|---|---|---|---|---|---|---|---|---|
| **QuiScore** | 57 | 59 | 59 | 61 | 71 | 65 | 78 | 74 | 63 |
| **Comment** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **QuiRating (£)** | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 | 100,000 |

**Activities :**

**1992 SIC UK codes :**

**Primary Code :**

5211 "Retail sale in non-specialised stores with food, beverages or tobacco predominating"

**Secondary Code(s) :**

5211 "Retail sale in non-specialised stores with food, beverages or tobacco predominating"

5

**1981 SIC UK codes :**

**Primary Code :**

6410 Food retailing

**Secondary Code(s) :**

64100 Food retailing
64800 "Retail distribution of household goods, hardware and ironmongery"
65400 Other specialised retail distribution (non-food)

**Trade Description :**

The retail distribution of food and home improvement and garden products.

Directors

| | | | |
|---|---|---|---|
| Mr K. McCarten | (7 24 57) | Marketing Director | 25 07 1999 |
| Miss R.P. Thorne | (2 12 62) | Finance Director | 25 07 1999 |
| Mr J.E. Adshead | (5 12 45) | Personnel Director | 25 07 1999 |
| Mr I.D. Coull | (6 7/50) | Director | 25 07 1999 |
| Mr D.B. Adriano | (4/24/43) | Director | 25 07 1999 |
| Sir T. Heiser | (5/24/32) | Director | 25 07 1999 |
| Mr C.M. Thompson | (4 4/43) | Director | 25 07/1999 |
| Sir D.G. Scholey | (6/28/35) | Director | 25/07/1999 |
| Mr D.M. Bremner | (10/18/57) | Director | 25 07/1999 |
| Sir G.J. Bull | (7/16/36) | Director | 25/07/1999 |
| Mr R.P. Whitbeac | (1/8/51) | Director | 25/07/1999 |
| Mr N.F. Matthews | (10/15/42) | Company Secretary | 25/07/1999 |

Holdings

There is no Holdings information available for this company.

Date of last change of name : 7 11/96

**Document filing dates**

| | |
|---|---|
| 17/06/1996 | Change in Mem & Arts |
| 25/11/1999 | Change in Share Capital |
| 02/12/1999 | Change of Directors |
| 30 11 1999 | K97 |
| 12 10 1999 | K98 |
| 26 07 1999 | K99 |
| 07 09 1993 | Charge Lodged |
| 14 04 1993 | Charge Lodged |
| 05 04 1993 | Charge Lodged |
| 09 09 1992 | Charge Lodged |
| 08 09 1992 | Charge Lodged |
| 25 03 1992 | Charge Lodged |
| 09 10 1991 | Charge Lodged |
| 05 12 1990 | Charge Lodged |
| 24 10 1990 | Charge Lodged |
| 03 08 1989 | Charge Lodged |
| 09 03 1995 | Mem.Satisfaction Lodged |
| 19 10 1994 | Mem.Satisfaction Lodged |
| 02 06 1993 | Mem.Satisfaction Lodged |
| 20 02 1992 | Mem.Satisfaction Lodged |
| 25 11 1991 | Mem.Satisfaction Lodged |
| 21 11 1991 | Mem.Satisfaction Lodged |
| 21 10 1991 | Mem.Satisfaction Lodged |
| 18 10 1991 | Mem.Satisfaction Lodged |
| 07 10 1991 | Mem.Satisfaction Lodged |
| 25 10 1990 | Mem.Satisfaction Lodged |
| 02 03 1990 | Mem.Satisfaction Lodged |
| 24 07 1999 | A c filed at CRO |
| 03 04 1999 | Accounts |
| 25 07 1999 | Annual Return |

**Bankers**
NATIONAL WESTMINSTER BANK PLC (60-70-04)

**Auditors**
PRICE WATERHOUSE COOPERS

**Previous Auditors**
COOPERS & LYBRAND (1997, 1996, 1995, 1994)
CLARK WHITEHILL (1993, 1992, 1991, 1990, 1989)

**Head Office :**
1. Stamford House
Stamford Street
Blackfriars

London

SE1 9LL
Phone Number : 0171 - 921 6000

**Trading Address :**

2. The Voucher Centre
Malvern Mill Waterford Street

Nelson
Lancashire
BB9 8AR
Phone Number : 01282 - 610683

3 19 Whitgift Centre

Croydon
Surrey
CR0 1UP
Phone Number : 020 - 86868067

4. 315 Commercial Rd

Portsmouth
Hampshire
PO1 4BS
Phone Number : 023 - 92822828

## Appendix E – Sample Financial Statements: Bankrupt Company

During the modelling process, 2,500 financial statements of companies were examined in detail. Recall that for each company, 54 financial and cash flow ratios were carried out before submitting them as inputs to neural networks. This analysis was conducted for each company irrespective of whether the company is already bankrupt or active. The following is a sample of the financial statements which relate to Waste Management Plc who went and their accounts were examined as part of the training sets.

WASTE MANAGEMENT INTERNATIONAL PLC

| | | | |
|---|---|---|---|
| **R/O Address :** | Grant Thornton House<br>Melton Street<br>London<br>NW1 2EP | **Registered No :**<br>**Type of company :**<br>**Date of incorporation :**<br>**Accounting Ref.Date :** | 02669336<br>Public, Not Quoted<br>09/12/1991<br>12/31 |
| **R/O Phone :** | 020 85 - 63 7000 | **Accounts Type :** | Group |
| **R/O Post Code :** | 020 85 - 63 7000 | **Company Status :** | Liquidation |
| **Latest Turnover :** | 1,087,596th GBP | **Number of Holdings :** | 0 |
| **Latest No of Employees :** | 15,540 | **Number of Subsid. :** | 0 |

**Activities :** *The provision of waste management and related services.*

**1992 SIC UK codes :**
- **Primary Code :** 5157 - Wholesale of waste and scrap
- **Secondary Code(s) :** 5157, 7415, 9000, 9305

**1981 SIC UK codes :**
- **Primary Code :** 9211 - "Refuse disposal, street cleaning, fumigation, etc."
- **Secondary Code(s) :** 62200, 92110

**Peer Group :** 5157 - Wholesale of waste and scrap ( VL : Very Large Companies)

| **PROFIT & LOSS ACCOUNT** | **31/12/1997**<br>12 months<br>th GBP | **31/12/1996**<br>12 months<br>th GBP | **31/12/1995**<br>12 months<br>th GBP | **31/12/1994**<br>12 months<br>th GBP | **31/12/1993**<br>12 months<br>th GBP | **31/12/1992**<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Turnover** | 1,087,596 | 1,218,894 | 1,181,000 | 1,115,653 | 941,419 | 816,551 |
| **UK Turnover** | | | | | | |
| **Overseas Turnover** | | | | | | |
| **Cost of Sales** | | | | | | |
| **Total Expenses** | -930,471 | -956,718 | -1,052,000 | | | |
| **Gross Profit** | 157,125 | 262,176 | 129,000 | | | |
| **Depreciation** | -87,379 | -97,351 | -88,000 | -76,215 | -57,695 | -52,396 |
| **Other Expenses** | | | -860,797 | -725,180 | | |
| **Operating Profit** | 69,746 | 164,825 | 41,000 | 178,641 | 158,544 | |
| **Other Income** | 12,834 | 39,344 | 42,000 | 32,931 | 37,635 | |
| **Exceptional Items** | -146,235 | | | | | |
| **Profit (Loss) before Interest** | 82,580 | 57,934 | 83,000 | 211,572 | 196,179 | 169,804 |
| **Interest Paid** | -18,890 | -45,492 | -60,000 | -46,415 | -45,324 | -26,139 |
| **Profit (Loss) before Tax** | 63,690 | 12,442 | 23,000 | 165,157 | 150,855 | 143,665 |
| **Taxation** | -25,029 | -59,979 | -11,000 | -40,735 | -41,064 | -48,043 |
| **Profit (Loss) after Tax** | 38,661 | -47,537 | 12,000 | 124,422 | 109,791 | 95,622 |
| **Extraordinary Items** | -17,363 | -18,662 | -16,000 | -20,189 | -10,519 | -13,309 |
| **Minority Interests** | | | | | | |
| **Profit (Loss) for Period** | 21,298 | -66,199 | -4,000 | 104,233 | 99,272 | 82,313 |
| **Dividends** | | | | | | |
| **Retained Profit(Loss)** | 21,298 | -66,199 | -3,000 | 104,233 | 99,272 | 82,313 |
| **Discontinued Operations** | | | | | | |
| **Audit Fee** | 1,201 | 1,317 | 1,000 | 1,284 | 1,225 | 936 |
| **Non-Audit Fee** | | | | | | |
| **Amortisation of Goodwill** | | | | | | |
| **Remuneration** | 324,473 | 397,412 | 398,000 | 370,597 | 340,365 | 192,505 |
| **Directors' Remuneration** | 1,326 | 1,294 | 1,000 | 569 | 1,033 | 517 |
| **Highest Paid Director** | 398 | 570 | | | | 369 |
| **Number of Employees** | 15,540 | 17,522 | 18,332 | 17,274 | 15,617 | 14,325 |

| **BALANCE SHEET** | **31/12/1997**<br>12 months<br>th GBP | **31/12/1996**<br>12 months<br>th GBP | **31/12/1995**<br>12 months<br>th GBP | **31/12/1994**<br>12 months<br>th GBP | **31/12/1993**<br>12 months<br>th GBP | **31/12/1992**<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Fixed Assets** | | | | | | |
| **Tangible Assets** | 653,851 | 766,819 | 845,000 | 754,932 | 621,914 | 448,068 |
| **Land & Building** | | | | | | |
| **Fixtures & Fittings** | | | | | | |
| **Plant & Vehicles** | | | | | | |
| **Other Fixed Assets** | | | | | | |
| **Intangible Assets** | | | | | | |
| **Investments** | 6,349 | 10,442 | 187,000 | 201,399 | 171,395 | 128,791 |
| **Fixed Assets** | 660,200 | 777,261 | 1,032,000 | 956,331 | 793,309 | 576,859 |
| **Current Assets** | | | | | | |
| **Stock & W.I.P.** | | | | | | |
| **Stock** | | | | | | |
| **W.I.P.** | | | | | | |
| **Trade Debtors** | 222,700 | 300,308 | 325,000 | 295,192 | 232,227 | 422,243 |
| **Bank & Deposits** | 36,652 | 40,891 | 38,000 | 35,146 | 27,354 | 34,671 |
| **Other Current Assets** | 183,266 | 424,980 | 253,000 | 272,300 | 234,513 | 57,067 |
| **Group Loans (asset)** | | | | | | |
| **Directors Loans (asset)** | | | | | | |
| **Other Debtors** | 133,043 | 177,623 | 173,000 | | | |
| **Investm. & Other Cur. Assets** | 50,223 | 247,357 | 80,000 | | | |
| **Current Assets** | 442,618 | 766,179 | 615,000 | 602,638 | 494,094 | 513,981 |
| **Current Liabilities** | | | | | | |
| **Trade Creditors** | -107,733 | -136,375 | -143,000 | -136,069 | -104,461 | -196,452 |
| **Short Term Loans & Overdrafts** | -63,444 | -188,583 | | | -88,889 | |
| **Bank Overdrafts** | 0 | 0 | | | | |
| **Group Loans (short t.)** | 0 | 0 | | | | |
| **Director Loans (short t.)** | 0 | 0 | | | | |
| **Hire Purch. & Leas. (short t.)** | 0 | 0 | | | | |
| **Hire Purchase (short t.)** | | | | | | |
| **Leasing (short t.)** | | | | | | |
| **Other Short Term Loans** | -63,444 | -188,583 | | | | |
| **Total Other Current Liabilities** | -227,212 | -204,113 | -554,000 | -367,955 | -162,412 | -185,231 |
| **Corporation Tax** | | -4,000 | | | | |
| **Dividends** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Accruals & Def. Inc. (sh. t.)** | -204,791 | -169,227 | -184,000 | | | |
| **Social Securities & V.A.T.** | | | | | | |
| **Other Current Liabilities** | -22,421 | -34,886 | -366,000 | | | |
| **Current Liabilities** | -398,389 | -529,071 | -696,000 | -504,024 | -355,762 | -381,683 |
| **Net Current Assets (Liab.)** | 44,229 | 237,108 | -81,000 | 98,614 | 138,332 | 132,298 |
| **Net Tangible Assets (Liab.)** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| **Working Capital** | 114,967 | 163,933 | 182,000 | 159,123 | 127,766 | 225,791 |
| **Total Assets** | 1,102,818 | 1,543,440 | 1,647,000 | 1,558,969 | 1,287,403 | 1,090,840 |
| **Total Assets less Cur. Liab.** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| **Long Term Liabilities** | | | | | | |
| **Long Term Debt** | -136,313 | -453,358 | -457,000 | -527,956 | -489,428 | -188,701 |
| **Group Loans (long t.)** | -668 | -90,376 | -90,000 | | | |
| **Director Loans (long t.)** | | | | | | |
| **Hire Purch. Leas. (long t.)** | | | | | | |
| **Hire Purchase (long t.)** | | | | | | |
| **Leasing (long t.)** | | | | | | |
| **Other Long Term Loans** | -135,645 | -362,982 | -367,000 | | | |
| **Total Other Long Term Liab.** | -222,830 | -246,109 | -222,000 | -224,967 | -186,239 | -98,469 |
| **Accruals & Def. Inc. (l. t.)** | 0 | 0 | 0 | | | |
| **Other Long Term Liab.** | 0 | 0 | 0 | | | |
| **Provisions for Other Liab.** | -222,830 | -246,109 | -222,000 | | | |
| **Deferred Tax** | -12,124 | -125,935 | | | | |
| **Other Provisions** | -210,706 | -120,174 | -222,000 | | | |
| **Balance Sheet Minorities** | | | | | -36,148 | -92,644 |
| **Long Term Liabilities** | -359,143 | -699,467 | -679,000 | -752,923 | -675,067 | -323,318 |
| **Total Assets less Liabilities** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |
| **Shareholders Funds** | | | | | | |
| **Issued Capital** | 37,527 | 37,527 | 38,000 | 37,508 | 37,501 | 37,500 |
| **Total Reserves** | 307,759 | 277,375 | 235,000 | 264,514 | 218,473 | 348,339 |
| **Share Premium Account** | 394,199 | 394,196 | 394,000 | | | |
| **Revaluation Reserves** | 0 | 0 | 0 | | | |
| **Profit (Loss) Account** | 335,763 | 314,465 | 381,000 | 384,123 | 279,890 | |
| **Other Reserves** | -422,203 | -431,286 | -540,000 | -119,609 | -61,417 | |
| **Shareholders Funds** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |

| CASH FLOW STATEMENT | 31/12/1997<br>12 months<br>th GBP | 31/12/1996<br>12 months<br>th GBP | 31/12/1995<br>12 months<br>th GBP | 31/12/1994<br>12 months<br>th GBP | 31/12/1993<br>12 months<br>th GBP | 31/12/1992<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Net Cash In(Out)flow Operat. Activ.** | 260,834 | 220,671 | 222,000 | | | |
| **Net Cash In(Out)flow Ret. on Invest.** | -28,335 | -36,536 | -42,000 | | | |
| **Taxation** | -15,796 | -19,283 | -15,000 | | | |
| **Net Cash Out(In)flow Investing Activ.** | | -124,000 | | | | |
| **Capital Expenditure & Financ. Invest.** | -74,193 | -109,842 | | | | |
| **Acquisition & Disposal** | 249,510 | 845 | | | | |
| **Equity Dividends Paid** | | | | | | |
| **Management of Liquid Resources** | 3,240 | -3,144 | | | | |
| **Net Cash Out(In)flow from Financing** | -397,643 | -47,412 | -40,000 | | | |
| **Increase(Decrease) Cash & Equiv.** | -2,383 | 5,299 | 1,000 | | | |

| FINANCIAL RATIOS | 31/12/1997 | 31/12/1996 | 31/12/1995 | 31/12/1994 | 31/12/1993 | 31/12/1992 |
|---|---|---|---|---|---|---|
| **Current Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Liquidity Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Shareholders Liquidity Ratio** | 0.96 | 0.45 | 0.40 | 0.40 | 0.38 | 1.19 |
| **Solvency Ratio (%)** | 31.31 | 20.40 | 16.51 | 19.37 | 19.88 | 35.37 |
| **Asset Cover** | 8.09 | 3.40 | 3.60 | 2.95 | 2.63 | 5.78 |
| **Gearing (%)** | 122.39 | 282.01 | 249.63 | 249.29 | 298.69 | 83.80 |
| **Shareholders Funds per Empl. (Unit)** | 22,219 | 17,972 | 14,837 | 17,484 | 16,391 | 26,935 |
| **Working Capital per Employee (Unit)** | 7,398 | 9,356 | 9,928 | 9,212 | 8,181 | 15,762 |
| **Total Assets per Employee (Unit)** | 70,966 | 88,086 | 89,843 | 90,249 | 82,436 | 76,149 |

| PROFITABILITY RATIOS | 31/12/1997 | 31/12/1996 | 31/12/1995 | 31/12/1994 | 31/12/1993 | 31/12/1992 |
|---|---|---|---|---|---|---|
| **Profit Margin (%)** | 5.86 | 1.02 | 1.95 | 14.80 | 16.02 | 17.59 |
| **Return on Shareholder Funds (%)** | 18.45 | 3.95 | 8.46 | 54.68 | 58.93 | 37.23 |
| **Return on Capital Employed (%)** | 9.04 | 1.23 | 2.42 | 15.66 | 16.19 | 20.26 |
| **Return on Total Assets (%)** | 5.78 | 0.81 | 1.40 | 10.59 | 11.72 | 13.17 |
| **Interest Cover** | 4.37 | 1.27 | 1.38 | 4.56 | 4.33 | 6.50 |
| **Stock Turnover** | | | | | | |
| **Debtors Turnover** | 4.88 | 4.06 | 3.63 | 3.78 | 4.05 | 1.93 |
| **Debtor Collection (days)** | 74.74 | 89.93 | 100.44 | 96.58 | 90.04 | 188.74 |
| **Creditors Payment (days)** | 36.16 | 40.84 | 44.20 | 44.52 | 40.50 | 87.81 |
| **Net Assets Turnover** | 1.54 | 1.20 | 1.24 | 1.06 | 1.01 | 1.15 |
| **Fixed Assets Turnover** | 1.65 | 1.57 | 1.14 | 1.17 | 1.19 | 1.42 |
| **Salaries/Turnover (%)** | 29.83 | 32.60 | 33.70 | 33.22 | 36.15 | 23.58 |
| **Turnover per Employee (Unit)** | 69,987 | 69,564 | 64,423 | 64,586 | 60,282 | 57,002 |
| **Average Remun. per Year (Unit)** | 20,880 | 22,681 | 21,711 | 21,454 | 21,795 | 13,438 |
| **Profit per Employee (Unit)** | 4,098 | 710 | 1,255 | 9,561 | 9,660 | 10,029 |

WASTE MANAGEMENT INTERNATIONAL PLC

| | | | |
|---|---|---|---|
| **R/O Address :** | Grant Thornton House<br>Melton Street<br>London<br>NW1 2EP | **Registered No :** | 02669336 |
| | | **Type of company :** | Public, Not Quoted |
| | | **Date of incorporation :** | 09/12/1991 |
| | | **Accounting Ref.Date :** | 12/31 |
| **R/O Phone :** | 020 85 - 63 7000 | **Accounts Type :** | Group |
| **R/O Post Code :** | 020 85 - 63 7000 | **Company Status :** | Liquidation |
| **Latest Turnover :** | 1,087,596th GBP | **Number of Holdings :** | 0 |
| **Latest No of Employees :** | 15,540 | **Number of Subsid. :** | 0 |

**Activities :** The provision of waste management and related services.

**1992 SIC UK codes :**
**Primary Code :** 5157 - Wholesale of waste and scrap
**Secondary Code(s) :** 5157, 7415, 9000, 9305

**1981 SIC UK codes :**
**Primary Code :** 9211 - "Refuse disposal, street cleaning, fumigation, etc."
**Secondary Code(s) :** 62200, 92110

**Peer Group :** 5157 - Wholesale of waste and scrap ( VL : Very Large Companies)

| **PROFIT & LOSS ACCOUNT** | **31/12/1997**<br>12 months<br>th GBP | **31/12/1996**<br>12 months<br>th GBP | **31/12/1995**<br>12 months<br>th GBP | **31/12/1994**<br>12 months<br>th GBP | **31/12/1993**<br>12 months<br>th GBP | **31/12/1992**<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Turnover** | 1,087,596 | 1,218,894 | 1,181,000 | 1,115,653 | 941,419 | 816,551 |
| **UK Turnover** | | | | | | |
| **Overseas Turnover** | | | | | | |
| **Cost of Sales** | | | | | | |
| **Total Expenses** | -930,471 | -956,718 | -1,052,000 | | | |
| **Gross Profit** | 157,125 | 262,176 | 129,000 | | | |
| **Depreciation** | -87,379 | -97,351 | -88,000 | -76,215 | -57,695 | -52,396 |
| **Other Expenses** | | | -860,797 | -725,180 | | |
| **Operating Profit** | 69,746 | 164,825 | 41,000 | 178,641 | 158,544 | |
| **Other Income** | 12,834 | 39,344 | 42,000 | 32,931 | 37,635 | |
| **Exceptional Items** | -146,235 | | | | | |
| **Profit (Loss) before Interest** | 82,580 | 57,934 | 83,000 | 211,572 | 196,179 | 169,804 |
| **Interest Paid** | -18,890 | -45,492 | -60,000 | -46,415 | -45,324 | -26,139 |
| **Profit (Loss) before Tax** | 63,690 | 12,442 | 23,000 | 165,157 | 150,855 | 143,665 |
| **Taxation** | -25,029 | -59,979 | -11,000 | -40,735 | -41,064 | -48,043 |
| **Profit (Loss) after Tax** | 38,661 | -47,537 | 12,000 | 124,422 | 109,791 | 95,622 |
| **Extraordinary Items** | -17,363 | -18,662 | -16,000 | -20,189 | -10,519 | -13,309 |
| **Minority Interests** | | | | | | |
| **Profit (Loss) for Period** | 21,298 | -66,199 | -4,000 | 104,233 | 99,272 | 82,313 |
| **Dividends** | | | | | | |
| **Retained Profit(Loss)** | 21,298 | -66,199 | -3,000 | 104,233 | 99,272 | 82,313 |
| **Discontinued Operations** | | | | | | |
| **Audit Fee** | 1,201 | 1,317 | 1,000 | 1,284 | 1,225 | 936 |
| **Non-Audit Fee** | | | | | | |
| **Amortisation of Goodwill** | | | | | | |
| **Remuneration** | 324,473 | 397,412 | 398,000 | 370,597 | 340,365 | 192,505 |
| **Directors' Remuneration** | 1,326 | 1,294 | 1,000 | 569 | 1,033 | 517 |
| **Highest Paid Director** | 398 | 570 | | | | 369 |
| **Number of Employees** | 15,540 | 17,522 | 18,332 | 17,274 | 15,617 | 14,325 |

| **BALANCE SHEET** | **31/12/1997**<br>12 months<br>th GBP | **31/12/1996**<br>12 months<br>th GBP | **31/12/1995**<br>12 months<br>th GBP | **31/12/1994**<br>12 months<br>th GBP | **31/12/1993**<br>12 months<br>th GBP | **31/12/1992**<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Fixed Assets** | | | | | | |
| **Tangible Assets** | 653,851 | 766,819 | 845,000 | 754,932 | 621,914 | 448,068 |
| **Land & Building** | | | | | | |
| **Fixtures & Fittings** | | | | | | |
| **Plant & Vehicles** | | | | | | |
| **Other Fixed Assets** | | | | | | |
| **Intangible Assets** | | | | | | |
| **Investments** | 6,349 | 10,442 | 187,000 | 201,399 | 171,395 | 128,791 |
| **Fixed Assets** | 660,200 | 777,261 | 1,032,000 | 956,331 | 793,309 | 576,859 |
| **Current Assets** | | | | | | |
| **Stock & W.I.P.** | | | | | | |
| **Stock** | | | | | | |
| **W.I.P.** | | | | | | |
| **Trade Debtors** | 222,700 | 300,308 | 325,000 | 295,192 | 232,227 | 422,243 |
| **Bank & Deposits** | 36,652 | 40,891 | 38,000 | 35,146 | 27,354 | 34,671 |
| **Other Current Assets** | 183,266 | 424,980 | 253,000 | 272,300 | 234,513 | 57,067 |
| **Group Loans (asset)** | | | | | | |
| **Directors Loans (asset)** | | | | | | |
| **Other Debtors** | 133,043 | 177,623 | 173,000 | | | |
| **Investm. & Other Cur. Assets** | 50,223 | 247,357 | 80,000 | | | |
| **Current Assets** | 442,618 | 766,179 | 615,000 | 602,638 | 494,094 | 513,981 |
| **Current Liabilities** | | | | | | |
| **Trade Creditors** | -107,733 | -136,375 | -143,000 | -136,069 | -104,461 | -196,452 |
| **Short Term Loans & Overdrafts** | -63,444 | -188,583 | | | -88,889 | |
| **Bank Overdrafts** | 0 | 0 | | | | |
| **Group Loans (short t.)** | 0 | 0 | | | | |
| **Director Loans (short t.)** | 0 | 0 | | | | |
| **Hire Purch. & Leas. (short t.)** | 0 | 0 | | | | |
| **Hire Purchase (short t.)** | | | | | | |
| **Leasing (short t.)** | | | | | | |
| **Other Short Term Loans** | -63,444 | -188,583 | | | | |
| **Total Other Current Liabilities** | -227,212 | -204,113 | -554,000 | -367,955 | -162,412 | -185,231 |
| **Corporation Tax** | | -4,000 | | | | |
| **Dividends** | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Accruals & Def. Inc. (sh. t.)** | -204,791 | -169,227 | -184,000 | | | |
| **Social Securities & V.A.T.** | | | | | | |
| **Other Current Liabilities** | -22,421 | -34,886 | -366,000 | | | |
| **Current Liabilities** | -398,389 | -529,071 | -696,000 | -504,024 | -355,762 | -381,683 |
| **Net Current Assets (Liab.)** | 44,229 | 237,108 | -81,000 | 98,614 | 138,332 | 132,298 |
| **Net Tangible Assets (Liab.)** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| ***Working Capital*** | 114,967 | 163,933 | 182,000 | 159,123 | 127,766 | 225,791 |
| **Total Assets** | 1,102,818 | 1,543,440 | 1,647,000 | 1,558,969 | 1,287,403 | 1,090,840 |
| **Total Assets less Cur. Liab.** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| **Long Term Liabilities** | | | | | | |
| **Long Term Debt** | -136,313 | -453,358 | -457,000 | -527,956 | -489,428 | -188,701 |
| **Group Loans (long t.)** | -668 | -90,376 | -90,000 | | | |
| **Director Loans (long t.)** | | | | | | |
| **Hire Purch. Leas. (long t.)** | | | | | | |
| **Hire Purchase (long t.)** | | | | | | |
| **Leasing (long t.)** | | | | | | |
| **Other Long Term Loans** | -135,645 | -362,982 | -367,000 | | | |
| ***Total Other Long Term Liab.*** | -222,830 | -246,109 | -222,000 | -224,967 | -186,239 | -98,469 |
| **Accruals & Def. Inc. (l. t.)** | 0 | 0 | 0 | | | |
| **Other Long Term Liab.** | 0 | 0 | 0 | | | |
| **Provisions for Other Liab.** | -222,830 | -246,109 | -222,000 | | | |
| **Deferred Tax** | -12,124 | -125,935 | | | | |
| **Other Provisions** | -210,706 | -120,174 | -222,000 | | | |
| **Balance Sheet Minorities** | | | | | -36,148 | -92,644 |
| **Long Term Liabilities** | -359,143 | -699,467 | -679,000 | -752,923 | -675,667 | -323,318 |
| **Total Assets less Liabilities** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |
| **Shareholders Funds** | | | | | | |
| **Issued Capital** | 37,527 | 37,527 | 38,000 | 37,508 | 37,501 | 37,500 |
| ***Total Reserves*** | 307,759 | 277,375 | 235,000 | 264,514 | 218,473 | 348,339 |
| **Share Premium Account** | 394,199 | 394,196 | 394,000 | | | |
| **Revaluation Reserves** | 0 | 0 | 0 | | | |
| **Profit (Loss) Account** | 335,763 | 314,465 | 381,000 | 384,123 | 279,890 | |
| **Other Reserves** | -422,203 | -431,286 | -540,000 | -119,609 | -61,417 | |
| **Shareholders Funds** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |

| CASH FLOW STATEMENT | 31/12/1997<br>12 months<br>th GBP | 31/12/1996<br>12 months<br>th GBP | 31/12/1995<br>12 months<br>th GBP | 31/12/1994<br>12 months<br>th GBP | 31/12/1993<br>12 months<br>th GBP | 31/12/1992<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Net Cash In(Out)flow Operat. Activ.** | 260,834 | 220,671 | 222,000 | | | |
| **Net Cash In(Out)flow Ret. on Invest.** | -28,335 | -36,536 | -42,000 | | | |
| **Taxation** | -15,796 | -19,283 | -15,000 | | | |
| **Net Cash Out(In)flow Investing Activ.** | | -124,000 | | | | |
| **Capital Expenditure & Financ. Invest.** | -74,193 | -109,842 | | | | |
| **Acquisition & Disposal** | 249,510 | 845 | | | | |
| **Equity Dividends Paid** | | | | | | |
| ***Management of Liquid Resources*** | 3,240 | -3,144 | | | | |
| **Net Cash Out(In)flow from Financing** | -397,643 | -47,412 | -40,000 | | | |
| **Increase(Decrease) Cash & Equiv.** | -2,383 | 5,299 | 1,000 | | | |

| *FINANCIAL RATIOS* | 31/12/1997 | 31/12/1996 | 31/12/1995 | 31/12/1994 | 31/12/1993 | 31/12/1992 |
|---|---|---|---|---|---|---|
| **Current Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Liquidity Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Shareholders Liquidity Ratio** | 0.96 | 0.45 | 0.40 | 0.40 | 0.38 | 1.19 |
| **Solvency Ratio (%)** | 31.31 | 20.40 | 16.51 | 19.37 | 19.88 | 35.37 |
| **Asset Cover** | 8.09 | 3.40 | 3.60 | 2.95 | 2.63 | 5.78 |
| **Gearing (%)** | 122.39 | 282.01 | 249.63 | 249.29 | 298.69 | 83.80 |
| **Shareholders Funds per Empl. (Unit)** | 22,219 | 17,972 | 14,837 | 17,484 | 16,391 | 26,935 |
| **Working Capital per Employee (Unit)** | 7,398 | 9,356 | 9,928 | 9,212 | 8,181 | 15,762 |
| **Total Assets per Employee (Unit)** | 70,966 | 88,086 | 89,843 | 90,249 | 82,436 | 76,149 |

| PROFITABILITY RATIOS | 31/12/1997 | 31/12/1996 | 31/12/1995 | 31/12/1994 | 31/12/1993 | 31/12/1992 |
|---|---|---|---|---|---|---|
| **Profit Margin (%)** | 5.86 | 1.02 | 1.95 | 14.80 | 16.02 | 17.59 |
| **Return on Shareholder Funds (%)** | 18.45 | 3.95 | 8.46 | 54.68 | 58.93 | 37.23 |
| **Return on Capital Employed (%)** | 9.04 | 1.23 | 2.42 | 15.66 | 16.19 | 20.26 |
| **Return on Total Assets (%)** | 5.78 | 0.81 | 1.40 | 10.59 | 11.72 | 13.17 |
| **Interest Cover** | 4.37 | 1.27 | 1.38 | 4.56 | 4.33 | 6.50 |
| **Stock Turnover** | | | | | | |
| ***Debtors Turnover*** | 4.88 | 4.06 | 3.63 | 3.78 | 4.05 | 1.93 |
| **Debtor Collection (days)** | 74.74 | 89.93 | 100.44 | 96.58 | 90.04 | 188.74 |
| **Creditors Payment (days)** | 36.16 | 40.84 | 44.20 | 44.52 | 40.50 | 87.81 |
| **Net Assets Turnover** | 1.54 | 1.20 | 1.24 | 1.06 | 1.01 | 1.15 |
| **Fixed Assets Turnover** | 1.65 | 1.57 | 1.14 | 1.17 | 1.19 | 1.42 |
| **Salaries/Turnover (%)** | 29.83 | 32.60 | 33.70 | 33.22 | 36.15 | 23.58 |
| **Turnover per Employee (Unit)** | 69,987 | 69,564 | 64,423 | 64,586 | 60,282 | 57,002 |
| **Average Remun. per Year (Unit)** | 20,880 | 22,681 | 21,711 | 21,454 | 21,795 | 13,438 |
| **Profit per Employee (Unit)** | 4,098 | 710 | 1,255 | 9,561 | 9,660 | 10,029 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **Accruals & Def. Inc. (sh. t.)** | -204,791 | -169,227 | -184,000 | | | |
| **Social Securities & V.A.T.** | | | | | | |
| **Other Current Liabilities** | -22,421 | -34,886 | -366,000 | | | |
| **Current Liabilities** | -398,389 | -529,071 | -696,000 | -504,024 | -355,762 | -381,683 |
| **Net Current Assets (Liab.)** | 44,229 | 237,108 | -81,000 | 98,614 | 138,332 | 132,298 |
| **Net Tangible Assets (Liab.)** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| **Working Capital** | 114,967 | 163,933 | 182,000 | 159,123 | 127,766 | 225,791 |
| **Total Assets** | 1,102,818 | 1,543,440 | 1,647,000 | 1,558,969 | 1,287,403 | 1,090,840 |
| **Total Assets less Cur. Liab.** | 704,429 | 1,014,369 | 951,000 | 1,054,945 | 931,641 | 709,157 |
| **Long Term Liabilities** | | | | | | |
| **Long Term Debt** | -136,313 | -453,358 | -457,000 | -527,956 | -489,428 | -188,701 |
| **Group Loans (long t.)** | -668 | -90,376 | -90,000 | | | |
| **Director Loans (long t.)** | | | | | | |
| **Hire Purch. Leas. (long t.)** | | | | | | |
| **Hire Purchase (long t.)** | | | | | | |
| **Leasing (long t.)** | | | | | | |
| **Other Long Term Loans** | -135,645 | -362,982 | -367,000 | | | |
| **Total Other Long Term Liab.** | -222,830 | -246,109 | -222,000 | -224,967 | -186,239 | -98,469 |
| **Accruals & Def. Inc. (l. t.)** | 0 | 0 | 0 | | | |
| **Other Long Term Liab.** | 0 | 0 | 0 | | | |
| **Provisions for Other Liab.** | -222,830 | -246,109 | -222,000 | | | |
| **Deferred Tax** | -12,124 | -125,935 | | | | |
| **Other Provisions** | -210,706 | -120,174 | -222,000 | | | |
| **Balance Sheet Minorities** | | | | | -36,148 | -92,644 |
| **Long Term Liabilities** | -359,143 | -699,467 | -679,000 | -752,923 | -675,667 | -323,318 |
| **Total Assets less Liabilities** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |
| **Shareholders Funds** | | | | | | |
| **Issued Capital** | 37,527 | 37,527 | 38,000 | 37,508 | 37,501 | 37,500 |
| **Total Reserves** | 307,759 | 277,375 | 235,000 | 264,514 | 218,473 | 348,339 |
| **Share Premium Account** | 394,199 | 394,196 | 394,000 | | | |
| **Revaluation Reserves** | 0 | 0 | 0 | | | |
| **Profit (Loss) Account** | 335,763 | 314,465 | 381,000 | 384,123 | 279,890 | |
| **Other Reserves** | -422,203 | -431,286 | -540,000 | -119,609 | -61,417 | |
| **Shareholders Funds** | 345,286 | 314,902 | 272,000 | 302,022 | 255,974 | 385,839 |

| CASH FLOW STATEMENT | **31/12/1997**<br>12 months<br>th GBP | **31/12/1996**<br>12 months<br>th GBP | **31/12/1995**<br>12 months<br>th GBP | **31/12/1994**<br>12 months<br>th GBP | **31/12/1993**<br>12 months<br>th GBP | **31/12/1992**<br>12 months<br>th GBP |
|---|---|---|---|---|---|---|
| **Net Cash In(Out)flow Operat. Activ.** | 260,834 | 220,671 | 222,000 | | | |
| **Net Cash In(Out)flow Ret. on Invest.** | -28,335 | -36,536 | -42,000 | | | |
| **Taxation** | -15,796 | -19,283 | -15,000 | | | |
| **Net Cash Out(In)flow Investing Activ.** | | -124,000 | | | | |
| **Capital Expenditure & Financ. Invest.** | -74,193 | -109,842 | | | | |
| **Acquisition & Disposal** | 249,510 | 845 | | | | |
| **Equity Dividends Paid** | | | | | | |
| **Management of Liquid Resources** | 3,240 | -3,144 | | | | |
| **Net Cash Out(In)flow from Financing** | -397,643 | -47,412 | -40,000 | | | |
| **Increase(Decrease) Cash & Equiv.** | -2,383 | 5,299 | 1,000 | | | |

| FINANCIAL RATIOS | **31/12/1997** | **31/12/1996** | **31/12/1995** | **31/12/1994** | **31/12/1993** | **31/12/1992** |
|---|---|---|---|---|---|---|
| **Current Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Liquidity Ratio** | 1.11 | 1.45 | 0.88 | 1.20 | 1.39 | 1.35 |
| **Shareholders Liquidity Ratio** | 0.96 | 0.45 | 0.40 | 0.40 | 0.38 | 1.19 |
| **Solvency Ratio (%)** | 31.31 | 20.40 | 16.51 | 19.37 | 19.88 | 35.37 |
| **Asset Cover** | 8.09 | 3.40 | 3.60 | 2.95 | 2.63 | 5.78 |
| **Gearing (%)** | 122.39 | 282.01 | 249.63 | 249.29 | 298.69 | 83.80 |
| **Shareholders Funds per Empl. (Unit)** | 22,219 | 17,972 | 14,837 | 17,484 | 16,391 | 26,935 |
| **Working Capital per Employee (Unit)** | 7,398 | 9,356 | 9,928 | 9,212 | 8,181 | 15,762 |
| **Total Assets per Employee (Unit)** | 70,966 | 88,086 | 89,843 | 90,249 | 82,436 | 76,149 |

| PROFITABILITY RATIOS | **31/12/1997** | **31/12/1996** | **31/12/1995** | **31/12/1994** | **31/12/1993** | **31/12/1992** |
|---|---|---|---|---|---|---|
| **Profit Margin (%)** | 5.86 | 1.02 | 1.95 | 14.80 | 16.02 | 17.59 |
| **Return on Shareholder Funds (%)** | 18.45 | 3.95 | 8.46 | 54.68 | 58.93 | 37.23 |
| **Return on Capital Employed (%)** | 9.04 | 1.23 | 2.42 | 15.66 | 16.19 | 20.26 |
| **Return on Total Assets (%)** | 5.78 | 0.81 | 1.40 | 10.59 | 11.72 | 13.17 |
| **Interest Cover** | 4.37 | 1.27 | 1.38 | 4.56 | 4.33 | 6.50 |
| **Stock Turnover** | | | | | | |
| **Debtors Turnover** | 4.88 | 4.06 | 3.63 | 3.78 | 4.05 | 1.93 |
| **Debtor Collection (days)** | 74.74 | 89.93 | 100.44 | 96.58 | 90.04 | 188.74 |
| **Creditors Payment (days)** | 36.16 | 40.84 | 44.20 | 44.52 | 40.50 | 87.81 |
| **Net Assets Turnover** | 1.54 | 1.20 | 1.24 | 1.06 | 1.01 | 1.15 |
| **Fixed Assets Turnover** | 1.65 | 1.57 | 1.14 | 1.17 | 1.19 | 1.42 |
| **Salaries/Turnover (%)** | 29.83 | 32.60 | 33.70 | 33.22 | 36.15 | 23.58 |
| **Turnover per Employee (Unit)** | 69,987 | 69,564 | 64,423 | 64,586 | 60,282 | 57,002 |
| **Average Remun. per Year (Unit)** | 20,880 | 22,681 | 21,711 | 21,454 | 21,795 | 13,438 |
| **Profit per Employee (Unit)** | 4,098 | 710 | 1,255 | 9,561 | 9,660 | 10,029 |

## Appendix F – Ratio and Cash Flow Analysis Tools

As part of the neural network modelling process, the author bought a financial data analysis software from Red Sun Associates Ltd, Redhill, Surrey. This tool was used in addition to the Ratio and Cash Flow analysis tool available with Jordans (FAME). Recall that FAME is a financial database on CD-ROM containing of the financial statements data of major British public and private companies. As such, these two tools make up the data analysis for ensuring accurate calculation of financial ratios. The selected company may then be displayed or printed in a variety of customisable formats. Once a company is selected, full statistical analysis, such as peer analysis, graphical representation of financial ratios and cash flow analysis, and company ratings can be produced instantaneously and accurately. The detailed analysis can be exported to other applications such as excel or ASCII files.


# fame for Windows™ User Guide

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## 1.1 What Is fame?

fame is a financial database on CD-ROM containing the information on **270,000** major public and private British companies from the JordanWatch™ and JordanSurvey™ databases. Up to 5 years of detailed financial information and some descriptive details are given. Coverage is divided between two discs:

disc a contains any company that satisfies any of the following criteria:

- **Turnover greater than £750,00**
- **Shareholders Funds greater than £750,000**
- **Profits Greater than £45,000**

There are approximately 110,000 such companies classified as JW.

disc b contains additional companies that satisfy the following criteria:

- **Turnover greater than £500,000**
- **Current Assets greater than £250,000**
- **Current Liabilities greater than £250,000**
- **Pre-Tax Profit greater than £25,000**

There are approximately 100,000 such companies classified as JS.

fame will allow you to search for companies by their name, number or by a combination of 65 other search criteria including:

| | |
|---|---|
| **SIC Code or Trade Description** | by Primary and/or Secondary codes or a Word index of trade descriptions. |
| **Geographic Location** | by region, county, town, or postcode for either the registered or trading addresses. |
| **Financial Data** | by specifying minimum and/or maximum values or growth/decreasing rates of 17 accounting items. |
| **Number of Employees** | by specifying minimum and/or maximum values or growth/decreasing rates. |
| **Ratios** | by specifying minimum and/or maximum values or growth/decreasing rates of 19 financial and profitability ratios. |
| **Credit Score** | by specifying minimum and/or maximum values indicating levels of risk for companies. |
| **Credit Rating** | by specifying minimum and/or maximum recommended credit levels in pounds. |
| **Company Type** | |
| **Date of Incorporation** | |
| **Holding Company / Subsidiary** | to find companies having a British or Foreign holding company or British subsidiary. |
| **Directors, Auditors, Bankers** | by selecting from an index of names. |

The selected companies may then be displayed or printed in a variety of customisable formats

# Appendix 1 Registration Of Companies In The UK

The information on the fame database has been compiled from records filed at Companies House in Cardiff, London and Edinburgh. Companies House was first established in England and Wales and separately in Scotland by the Joint Stock Companies Act of 1844 which enabled companies to gain statutory recognition by a simple act of registration. There have been many Acts amending and consolidating company legislation since 1844, culminating in the 1985 Companies Act.

Companies House provides both the legal framework within which all companies operate and the means by which those companies are formally registered (incorporated) and dissolved.

The three main statutory duties of Companies House are to:

- incorporate and dissolve companies
- examine and file documents required under the Companies Act
- make company records available to the public

Once a company has been registered it is allowed a period of up to 18 months before having to file its Annual Accounts, which are from then on required to be filed on an annual basis. If companies persist in not filing their Annual Returns and Accounts, they can not only be removed from the Register but they may under certain circumstances have their directors prosecuted.

Under companies legislation, any person or persons associated for a lawful purpose may form an incorporated company with or without limited liability. There are four types of companies:

I) A private company limited by shares, where the liability is limited to the amount of share capital its members have agreed to pay.

ii) A private company limited by guarantee, where the liability is limited to the amount its members have undertaken to contribute to the assets of the company in the event of it being wound up.

iii) A private unlimited company, where there is no limit to the liability of its members.

iv) A public company, must be incorporated with a share capital of at least the authorised minimum (£50,000). At least a quarter of this must be paid when the company is formed.

**Registered Company Number**

The Registered Company Number is the number under which the company is registered at Companies House. There are some prefixes to the numbers which are as follows:

**1) Companies registered in England and Wales**

| | |
|---|---|
| No Code | Companies registered under the Companies Act. Since most companies are registered under the Companies Act, there are only a few companies with a prefix |
| AC | Assurance Company |
| FC | Oversees company which appears to have a place of business in England and Wales |
| IP | Industrial and Provident Society |
| LP | Limited Partnership |
| OC | Other Company |
| RC | Incorporated by Royal Charter or Letters Patent |
| ZC | Companies incorporated under other than the Companies Act |

**2) Companies registered in Scotland**

| | |
|---|---|
| SA | Assurance Company |
| SC | Companies registered under the Companies Act |
| SF | Overseas company which appears to have a place of business in Scotland |
| SL | Limited Partnership |
| SO | Other Company |
| SP | Industrial and Provident Society |
| SR | Incorporated by Royal Charter of Letters Patent |
| SZ | Companies incorporated under other than the Companies Act |

**3) Companies registered in Northern Ireland**

| | |
|---|---|
| NA | Assurance Company |
| NF | Overseas company which appears to have a place of business in Northern Ireland |
| NI | Companies registered under the Companies Act |
| NL | Limited Partnership |
| NO | Other Company |
| NP | Industrial and Provident Society |
| NR | Incorporated by Royal Charter or Letters Patent |
| NZ | Companies incorporated under other than the Companies Act |

**Types of Accounts**

1)Full Accounts

There will be a full set of figures for both the Balance Sheet and the Profit and Loss Account.

2)Abridged Accounts

Companies are permitted to file accounts in a modified form without detailed Profit and Loss Account if they can fulfil certain criteria defined in the 1985 Companies Act.

3)Small Companies

A small company must satisfy two of the following criteria and needs only to submit an abridged balance sheet:

- Turnover of less than £2.8 million
- Balance Sheet total not exceeding £1.4 million
- Number of employees not exceeding 50

4)Medium Companies

A medium-sized company must satisfy two of the following criteria and does not need to disclose a turnover figure:

- Turnover of less than £11.2 million
- Balance sheet total not exceeding £5.6 million
- Number of employees not exceeding 250

5)Dormant Accounts

Dormant companies can now file dormant accounts which do not need to be audited.

NOTE: The above exemptions are not available for publicly quoted companies, banking, insurance or shipping companies and any of their subsidiaries regardless of size. Fuller accounts may have been made available to the shareholders.

# Appendix 2 Jordans Company Classification

## JW Jordan Watch Company

A company that has: > £750,000 turnover
or > £45,000 pre-tax profit
or > £750,000 shareholders funds

Full financial details are available.

## JS Jordan Survey Company

A company that has: >£500,00 turnover
or >£250,000 current Assets
or >£250,000 current Liabilities
or >£25,000 pre-tax profit

## OS Other Subsidiary Company, OH Other Holding Company

Companies mentioned as a holding or a subsidiary within the record of a JW or JS company but for which accounts are not available in the database. Registered address, date of incorporation, and filing dates (but no separate accounts for the OS or OH Company) are given within the associated JW or JS record.

## FH Foreign Holding Company, FS Foreign Subsidiary Company

Companies listed within a JW or JS record. Country of origin but no accounts are given.

## PN Previous Name

This code appears in the main company index and allows you to search for a company if you only know its previous name. Recent name changes are listed in the index but the new name appears at the top of its record. Name changes are listed in the Miscellaneous Data section of the complete company record.

## 5.1 Displaying A Company Report

A complete company report contains full details of the company as received at Companies House, and includes the financial details for the latest five years (where they exist) and the average of those five years. See section 2.2 for full details of information available.

To view the reports of the companies selected from a search **click** on [Company Report] from the 'Summary of the Search' screen.

If a search results in only one company being selected, the company's complete report is automatically displayed.

The following buttons appear at the left in the tool bar at the bottom of the screen of the company report

| | |
|---|---|
| ◀ | Show previous company |
| ▶ | Show next company |
| ▤ | Returns user to the list of companies |

## 2.1 Coverage

Jordans has put together one of the largest and most complete financial databases of British companies. Jordans' financial database of the Major Public and Private British Companies is contained on the fame CD-ROM. The database has been compiled from records filed at Companies House in Cardiff, London and Edinburgh and supplemented with information taken from the London and Edinburgh Gazettes. The information that is included on the fame CD-ROM is carefully checked by the financial analysts of Jordans.

Jordans endeavours to give full information on as many companies as possible with a turnover in excess of £500,000 per year. However, many companies which fall into this category are not required by law to declare a turnover figure. As the law stands currently, small and medium sized companies are allowed to file modified accounts provided that they fulfil certain criteria.

Small companies which satisfy two of the following requirements:

- turnover less than £2,800,000
- balance sheet total not exceeding £1,400,000
- number of employees not exceeding 50

These companies need only submit an abridged balance sheet.

Medium sized companies which satisfy two of the following requirements:

- turnover less than £11,200,000
- balance sheet total not exceeding £5,600,000
- number of employees not exceeding 250

These companies do not need to disclose turnover.

Financial information is generally made available in the database on companies meeting at least one of the following criteria:

JW (Jordan Watch)

**Turnover greater than £750,00**
**Shareholders Funds greater than £750,000**
**Profits Greater than £45,000**

There are approximately 110,000 such companies.

JS (Jordan Survey)

**Turnover greater than £500,000**
**Current Assets greater than £250,000**
**Current Liabilities greater than £250,000**
**Pre-Tax Profit greater than £25,000**

## 2.2 Information Available

The information for companies on fame has been grouped into 12 different files.

### 2.2.1 The Company Profile

The Company Profile is a summary of the company, showing the company name, the Registered Company Number and:

- type of company (Private, Public Quoted, Public Unquoted, Unlisted Securities Market, Quoted Investment Trust, A.I.M.)
- the type of Jordans company classification (e.g. JW or JS)
- type of account
- status (live/dissolved/receivership/liquidation e.t.c.)
- accounting reference date
- date of incorporation
- the Registered Office address and telephone number
- the business sector
- nine selected financial data items
- the number of employees

### 2.2.2 Registered office address

This is where the company resides from an official point of view. It may also have one or more trading addresses.

### 2.2.3 Trading address

This is an address from which the company actively trades. A company can have more than one trading address.

### 2.2.4 SIC codes and trade description

SIC codes are the five digit UK Standard Industrial Classification Code (revised 1980). The classification to 4 digits is shown in Appendix 3.

A trade description and 4 digit primary UK SIC codes are assigned to each record according to the description of business activity given in the director's report in the company's published accounts. Additional 5 digit SIC codes may also be given. Since the SIC codes are not always a precise tool for classification, the description provides a more reliable guide to activity and is searchable for every company on the database with full financial details. In the case of conglomerates and diversified companies, where possible the core activities are selected, and up to a maximum of ten codes are given.

### 2.2.5 Profit and Loss Account and Number of Employees

Where available, up to five years data and the averages are given. The averages are computed by Bureau van Dijk using an arithmetical average for all the available years for the items of the accounts and for the ratios. For the trends, the calculations are based on the average calculated on the basis of a logarithmic least squared approximation. If the average figures have been adjusted to 12 months to take account of a variation in the number of months in the trading period, this is indicated by an asterisk (*).

### 2.2.6 Balance Sheet

Where available, up to 5 years of data and averages are given. The averages are computed by Bureau van Dijk using an arithmetical average for all the available years for the items of the accounts and for the ratios. For the trends, the calculations are based on the average calculated on the basis of a logarithmic least squared approximation. If the figures have been adjusted to 12 months to take account of the number of months in the trading period, this is indicated by an asterisk (*).

### 2.2.7 Ratios and Trends

Ratios and trends for up to 5 years and their averages are given. Year on year changes and absolute figures are included. If the average figures have been adjusted to 12 months to take account of a variation on the number of months in the trading period, this is indicated by an asterisk (*).

The formulae used for the calculation of the ratios and trends are contained in Appendix 5

### 2.2.8 Credit Score and Rating

Calculated by a formula supplied by Qui Credit Assessment Limited to give a measure of likelihood of company failure and to act as a yardstick which assists the calculation of credit limits. See Section 1.4

### 2.2.9 Names of the Principal Directors

All directors listed in the annual return are given including their stated job title. The year of the document used is indicated.

The Chairman and Company Secretary are indicated if known.

### 2.2.10 Names of Holding Companies

Their registered company number, or their country if they are foreign, and the type of relationship with the company.

### 2.2.11 Names of Subsidiaries

Their registered company number and address, type of relationship with the company, accounts filing date and date of incorporation.

### 2.2.12 Miscellaneous data

- accounts made-up date
- Jordans accounting date
- annual return date
- Jordans annual return date
- date of last transaction at Companies House
- date of last change of name
- documents filing dates
- bankers
- auditors
- trading addresses and telephone number

## 2.3 Data Presentation And Validation

The presentation of the information follows a tried and tested approach, recognised and approved by leading accountancy bodies and practitioners in the field.

The layout of the data is designed for ease of comprehension, and uses terminology widely accepted in the financial world.

The emphasis is on both consistency in the treatment of accounts, and accuracy in the recording of data. The overriding aim is to provide information in a form which can be compared meaningfully between companies and, within the same company, between different years.

The data entry procedures include rigorous checking of individual records and updates as they are entered, with many of the data fields subject to automatic validation on entry. Information on financial and performance ratios is calculated automatically using standard formulae, which are explained in detail in Appendix 5.

## 2.4 Updating

The Jordans database is updated daily, using information received from Companies House. This is supplemented by information taken from the London and Edinburgh Gazettes in order to provide the very latest information on the filing of certain time critical documents, including those relating to liquidation, receivership etc.

Accounts are updated annually, subsequent to their being made available on the public record at Companies House. There is an inevitable delay in processing the accounts at Companies House, and time is also needed to incorporate this information into our database. This time is kept to an absolute minimum.

When accounts of a company have been updated on the most recent CD-ROM, there is an asterisk (*) after the company name in the main index.

Information on directors is updated from the annual return when they are filed at Companies House.

When reviewing the latest accounts, in order to extract the relevant data Jordans normally considers only the latest year's figures, and does not revise the figures for earlier years without good reason, even when these are represented in an amended form along with the current set of accounts.

## 2.5 Consolidated Accounts

In the case of groups of companies with a common parent company, where possible the consolidated (group) account will be made available, along with the accounts of the principal subsidiaries. This is done partly to minimise the risk of "double counting" when carrying out inter-company comparisons. The relationship between individual holding and subsidiary companies is clearly indicated in the database, and this includes an indication of foreign holding companies. Foreign holding companies registered in the United Kingdom are not obliged to file accounts at Companies House in pounds sterling and so these will not be found in the database.

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# RATIO and CASHFLOW Analysis Software

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## CONTENTS



PC REQUIREMENTS

100% IBM compatible PC, 386 or faster, 2Mb RAM (recommend 4Mb or more), 3.5" floppy drive, 5Mb free hard disk space, DOS 5.0 or later, EGA/VGA monitor. Optional (recommended) Microsoft mouse or compatible pointing device. This is a powerful DOS application which many users run under Windows, PIF and Icon file supplied.

# RATIO and CASHFLOW Analysis Software

*Version 3*

## SOFTWARE EXPLANATION AND OVERVIEW

### The primary Help screen of the software is reproduced below.

<u>**Software Overview**</u>

This software reduces sets of financial data to understandable common proportions through RATIO and CASHFLOW analysis, to assist informed decision making and optimise your most valuable asset - your time. Design parameters included:

| | |
|---|---|
| **True Ratio breadth** | providing unrivalled coverage |
| **Structured Cashflow** | FRS1 (Revised 1996) format |
| **Impressive performance** | comprehensive information in seconds |
| **Concise results** | structured non superfluous output. |
| **Simplicity of use** | negates the need for user manuals |
| **Self contained** | no costly "add-on" modules. |

Information is input/imported to "Profit & Loss" PL, "Balance Sheet" BS and "Additional Data" AD templates.

Upto 45 ratios plus the original input data are saved to RT files, upto five of which may be merged to RM files for comparative or time series analysis; key element indexation is provided for the latter. The P&L account in RM files can be expressed as % constituents to emphasise performance.

Cashflow analysis also utilises the PL BS and AD files mentioned above. To yield a full picture upto five years accounting information may be analysed concurrently, the result is saved to a two page CF file.

Print and Export functions cover all user input files ie PL BS and AD files, plus the comprehensive software generated RT RM and CF files.

<u>**Menu Bar Items**</u>

Menu Bar items which appear at the head of the screen, are selectable by mouse and/or keyboard. Horizontal movement over the menu bar using the arrow keys, generates item explanation at the screen base.

| | |
|---|---|
| **Help** | advisory screen you are currently viewing |
| **Ratios** | explanation of Ratio analysis and the Ratios produced |
| **Cashflow** | explanation of Cashflow and the analysis produced |
| **Templates** | view "P&L", "BalSheet" & "AddtlData" templates. |
| **Form** | form a file into which data will be entered |
| **Load** | load a file you previously created |
| **Analyse** | access the Analysis functions of the software |
| **Utilities** | access Copy, Rename, List, Delete, Import & Export |
| **Print** | access the comprehensive reporting facilities |
| **Exit** | leave the program |

## SOFTWARE EXPLANATION AND OVERVIEW continued

**Demonstration Files** provided to assist user familiarisation with the software are listed below, these may be deleted if so desired when finished with.

| | |
|---|---|
| **5 sets of Accounts:** | PLdemo1, BSdemo1 and ADdemo1 |
| | PLdemo2, BSdemo2 and ADdemo2 |
| PL = P&Loss | PLdemo3, BSdemo3 and ADdemo3 |
| BS = BalSheet | PLdemo4, BSdemo4 and ADdemo4 |
| AD = AddtlData | PLdemo5, BSdemo5 and ADdemo5 |
| **Ratio Analysis files:** | RTdemo1, RTdemo2.......RTdemo5 |
| RTdemo1 analyses | PLdemo1, BSdemo1 and ADdemo1 |
| RTdemo2 analyses | PLdemo2, BSdemo2 and ADdemo2 etc |
| **Merged Ratio file:** | RMdemo comprising RTdemo5.....RTdemo1 |
| **Cashflow file:** | CFdemo analyses the 5 sets of accounts |

**Data Importation**

The RedSun software disk contains four ASCII text files relevant to the subject of importing data to the software. The file IMPORT.txt explains fully how to import data. The files IMPPL.txt IMPBS.txt and IMPAD.txt show the correct structure of import files and are based on the PLdemo1 BSdemo1 and ADdemo1 accounts files.

**Familiarisation**

Familiarise yourself with the software, by working through the Main Menu items in the sequence displayed. Use the demonstration files to see the workings of commands Load, Analyse, Print. Under UTILITIES, you may test the Copy command using the demonstration files, then test List, Rename, Delete, Export on the file(s) you have created via Copy.

Help is available at all important selection/action stages. All screens displayed to the user carry clear instructions. All "pop up" boxes are headed and contain textual usage notes. User actions often result in "on screen messages" being displayed in the lower right of the screen - this occurs on completion of certain actions and to advise the user of any inappropriate action/choice.

You may notice the absence of a SAVE command; the software automatically saves your files after creation/modification and prior to exiting.

Full functionality is available whether you elect to use the keyboard, a mouse or a combination of the two in operating the software.

---

Any comments concerning the design, operation and features of this software and/or suggestions relating to potential enhancements you may like to see included, would be most welcome.

RedSun Associates Ltd.

# RATIO and CASHFLOW Analysis Software

**Version 3**

## RATIOS PRODUCED AND INFORMATION SOURCE

| | P=P&Loss B=BalSheet A=AddtlData | SOURCE | EXPRESSED AS |
|---|---|---|---|
| **LIQUIDITY** | CURRENT RATIO | - B - | x factor |
| | QUICK RATIO | - B - | x factor |
| | TRADE DEBTORS TO TRADE CREDITORS | - B - | x factor |
| | WORKING CAPITAL TO SALES | P B - | percentage |
| | WORKING ASSETS TO SALES | P B - | percentage |
| **GEARING** | DEBT/EQUITY | - B - | percentage |
| | DEBT/ASSETS EMPLOYED | - B - | percentage |
| | INTEREST COVER | P - - | x factor |
| **PROFITABILITY** | RETURN ON CAPITAL EMPLOYED (ROCE) | P B - | percentage |
| | RETURN ON SHAREHOLDERS FUNDS (ROSF) | P B - | percentage |
| | RETURN ON EQUITY | P B - | percentage |
| | RETURN ON EQUITY AFTER EXT.ITEMS | P B - | percentage |
| | RETURN ON TOTAL ASSETS | P B - | percentage |
| | OPERATING PROFIT MARGIN | P - - | percentage |
| | NET PROFIT | P - - | percentage |
| | COST OF SALES TO TURNOVER | P - - | percentage |
| | GROSS PROFIT MARGIN | P - - | percentage |
| | OTHER VARIABLE DIRECT COSTS TO TURNOVER | P - - | percentage |
| | CONTRIBUTION MARGIN (CS RATIO) | P - - | percentage |
| | OVERHEADS TO TURNOVER | P - - | percentage |
| | EFFECTIVE TAX RATE | P - - | percentage |
| **ASSET ACTIVITY** | STOCK TURNOVER | P - - | x factor |
| | DAYS STOCK IN HAND | P - - | days |
| | DEBTORS TURNOVER | P B - | x factor |
| | DEBTORS DAYS (AV.COLLECTION PERIOD) | P B - | days |
| | CREDITORS DAYS (AV.PAYMENT PERIOD) | P B - | days |
| **PRODUCTIVITY** | ASSET TURNOVER | P B - | x factor |
| | TOTAL ASSET TURNOVER | P B - | x factor |
| | FIXED ASSET TURNOVER | P B - | x factor |
| | CURRENT ASSET TURNOVER | P B - | x factor |
| | NET CURRENT ASSET TURNOVER | P B - | x factor |
| | NET ASSET TURNOVER | P B - | x factor |
| | ACCUMULATED DEPRECIATION TO FIXED ASSETS | - B - | percentage |
| | DEPRECIATION CHARGE TO FIXED ASSETS | P B - | percentage |
| | PAYROLL COSTS PER EMPLOYEE | - - A | £ per employee |
| | TURNOVER PER EMPLOYEE | P - A | £ per employee |
| | TOTAL INCOME PER EMPLOYEE | P - A | £ per employee |
| | CONTRIBUTION PER EMPLOYEE | P - A | £ per employee |
| **INVESTORS** | EARNINGS PER SHARE (EPS) | P - A | pence |
| | PRICE/EARNINGS RATIO (P/E) | P - A | x factor |
| | DIVIDEND PER ORDINARY SHARE | P - A | pence |
| | DIVIDEND PAYOUT | P - - | percentage |
| | DIVIDEND YIELD | P - A | percentage |
| | DIVIDEND COVER | P - - | x factor |
| | EQUITY PER ORDINARY SHARE | - B A | £ per share |
| **RATIO SUMMARY** | Number of ratios produced: 45 ratios assuming files | P B A | available |
| | 36 ratios assuming files | P B - | available |
| | 21 ratios assuming files | P - A | available |
| | 13 ratios assuming file | P - - | available |
| | 7 ratios assuming files | - B A | available |
| | 6 ratios assuming file | - B - | available |

## RATIO ANALYSIS OUTPUT: RATIOS

| Rmdemo1 01.05.97 15:42:22 | | | | | | | |
|---|---|---|---|---|---|---|---|
| | FILE NAME | : | Rtdemo5 | Rtdemo4 | Rtdemo3 | Rtdemo2 | Rtdemo1 |
| | Date | : | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 |
| | Time | : | 15:41:42 | 15:41:40 | 15:41:38 | 15:41:35 | 15:41:33 |
| | P&Loss | : | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 | Pldemo1 |
| | BalSheet | : | Bsdemo5 | Bsdemo4 | Bsdemo3 | Bsdemo2 | Bsdemo1 |
| | AddtlData | : | Addemo5 | Addemo4 | Addemo3 | Addemo2 | Addemo1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **LIQUIDITY** | | | | | | |
| Current | x | 1.56 | 1.59 | 1.55 | 1.73 | 1.12 |
| Quick | x | 1.23 | 1.25 | 1.22 | 1.35 | .86 |
| Debtors:Creditors | x | 2.33 | 2.51 | 2.34 | 2.53 | 1.88 |
| Wkg Capital:Sales | % | 8.56 | 9.18 | 9.63 | 9.86 | 2.34 |
| Wkg Assets :Sales | % | 10.94 | 11.95 | 13.30 | 13.28 | 12.03 |
| **GEARING** | | | | | | |
| Debt/Equity | % | 22.86 | 50.90 | 131.65 | 220.46 | 110.26 |
| Debt/Assets Empld | % | 14.91 | 26.46 | 43.01 | 52.89 | 27.84 |
| Interest Cover | x | 14.89 | 8.65 | 3.67 | 3.85 | 3.52 |
| **PROFITABILITY** | | | | | | |
| ROCE | % | 28.61 | 25.43 | 15.98 | 19.77 | 11.33 |
| ROSF | % | 42.89 | 44.84 | 37.33 | 58.77 | 32.14 |
| Rtn Equity | % | 30.52 | 32.99 | 27.93 | 45.04 | 26.03 |
| Rtn Equity E.Itms | % | 36.71 | 32.99 | 27.93 | 17.28 | 26.03 |
| Rtn Total Assets | % | 15.75 | 13.82 | 8.49 | 11.10 | 5.04 |
| Op.Profit Margin | % | 6.34 | 6.03 | 3.07 | 4.15 | 3.35 |
| Net Profit | % | 5.75 | 3.55 | 1.79 | .76 | .91 |
| Cost Sales: T/O | % | 56.16 | 55.75 | 54.23 | 54.42 | 55.48 |
| Gross Prft Margin | % | 43.84 | 44.25 | 45.77 | 45.58 | 44.52 |
| OVarDirCosts: T/O | % | 5.59 | 4.51 | 4.82 | 5.66 | 5.04 |
| Ctbtn Margin (CS) | % | 38.24 | 39.74 | 40.95 | 39.92 | 39.48 |
| OHds:Turnover | % | 31.91 | 33.71 | 37.88 | 35.77 | 36.13 |
| Eff Tax Rate | % | 22.00 | 20.00 | 20.00 | 20.00 | 10.00 |
| **ASSET ACTIVITY** | | | | | | |
| Stock T/Over | x | 11.38 | 11.02 | 9.87 | 10.90 | 11.49 |
| Days Stock InHand | d | 32.71 | 34.23 | 38.13 | 34.10 | 33.30 |
| Debtors T/Over | x | 9.67 | 8.94 | 7.50 | 7.38 | 6.71 |
| Debtors Days | d | 37.75 | 40.84 | 48.66 | 49.48 | 54.36 |
| Creditors Days | d | 46.53 | 47.00 | 59.93 | 55.41 | 81.87 |
| **PRODUCTIVITY** | | | | | | |
| Asset T/Over | x | 3.93 | 4.44 | 4.75 | 4.94 | 7.01 |
| Total Asset T/Over | x | 2.56 | 2.76 | 2.74 | 3.16 | 3.36 |
| Fixed Asset T/Over | x | 6.59 | 8.70 | 10.77 | 12.00 | 12.57 |
| Current Ass T/Over | x | 4.18 | 4.05 | 3.67 | 4.28 | 4.58 |
| Net Cur Ass T/Over | x | 11.68 | 10.89 | 10.39 | 10.14 | 42.80 |
| Net Asset T/Over | x | 5.38 | 7.55 | 12.27 | 17.06 | 25.26 |
| Acc Dep Fxd Assets | % | 52.33 | 49.38 | 43.21 | 31.40 | 21.46 |
| Dep Chg Fxd Assets | % | 11.04 | 11.99 | 11.81 | 11.81 | 11.88 |
| Payroll/Employee | £ | 24607.03 | 24113.04 | 22504.90 | 21637.52 | 19383.40 |
| TurnOver/Employee | £ | 97351.03 | 96551.21 | 77828.13 | 84325.34 | 78957.80 |
| T.Income/Employee | £ | 98270.83 | 97023.25 | 78057.27 | 84402.62 | 78957.80 |
| Contrbtn/Employee | £ | 37229.57 | 38373.32 | 31870.03 | 33664.38 | 31173.47 |
| **INVESTORS** | | | | | | |
| Earnings per Share | p | 355.87 | 261.22 | 224.43 | 136.91 | 222.06 |
| Price Earnings | x | .66 | .68 | .69 | .37 | .30 |
| Div/Ordinary Share | p | 20.00 | 21.25 | 15.00 | 13.33 | 6.00 |
| Dividend Payout | % | 5.62 | 8.13 | 6.68 | 9.74 | 2.70 |
| Dividend Yield | % | .09 | .11 | .09 | .09 | .08 |
| Dividend Cover | x | 17.79 | 12.29 | 14.96 | 10.27 | 37.01 |
| Equity/OrdShare | £ | 9.69 | 7.92 | 8.04 | 7.92 | 8.53 |

## RATIO ANALYSIS OUTPUT: KEY TREND INDEX

KEY TREND INDEX
***************

| RMdemo1 01.05.97 15:42:22 | FILE NAME | : | Rtdemo5 | Rtdemo4 | Rtdemo3 | Rtdemo2 | Rtdemo1 |
|---|---|---|---|---|---|---|---|
| | Date | : | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 |
| | Time | : | 15:41:42 | 15:41:40 | 15:41:38 | 15:41:35 | 15:41:33 |
| | P&Loss | : | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 | Pldemo1 |
| | BalSheet | : | Bsdemo5 | Bsdemo4 | Bsdemo3 | Bsdemo2 | Bsdemo1 |
| | AddtlData | : | Addemo5 | Addemo4 | Addemo3 | Addemo2 | Addemo1 |
| TURNOVER TOTAL | | | 123 | 114 | 99 | 103 | 100 |
| GROSS PROFIT | | | 121 | 113 | 101 | 106 | 100 |
| CONTRIBUTION | | | 119 | 115 | 102 | 104 | 100 |
| OVERHEADS TOTAL | | | 109 | 106 | 103 | 102 | 100 |
| OPERATING PROFIT | | | 234 | 206 | 91 | 128 | 100 |
| PROFIT BEFORE INT+TAX | | | 556 | 405 | 205 | 256 | 100 |
| PROFIT BEFORE TAXATION | | | 774 | 534 | 232 | 276 | 100 |
| DIVIDENDS Ordinary | | | 1667 | 1417 | 500 | 333 | 100 |
| TOTAL FIXED ASSETS | | | 235 | 165 | 115 | 108 | 100 |
| NET CURRENT ASSETS | | | 452 | 448 | 406 | 436 | 100 |
| CAPITAL EMPLOYED | | | 220 | 180 | 146 | 147 | 100 |
| NET ASSETS | | | 579 | 382 | 203 | 153 | 100 |

# RATIO and CASHFLOW Analysis Software

Version 3

## RATIO ANALYSIS OUTPUT: P&L % ANALYSIS

P&L % ANALYSIS
***************

| RMdemo1 01.05.97 15:42:22 | FILE NAME | Rtdemo5 | Rtdemo4 | Rtdemo3 | Rtdemo2 | Rtdemo1 |
|---|---|---|---|---|---|---|
| | Date | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 | 01.05.97 |
| | Time | 15:41:42 | 15:41:40 | 15:41:38 | 15:41:35 | 15:41:33 |
| | P&Loss | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 | Pldemo1 |
| **TURNOVER TOTAL** | | 100.00 % | 100.00 % | 100.00 % | 100.00 % | 100.00 % |
| **COST OF SALES** | | | | | | |
| Opening Stock | | 4.84 % | 4.89 % | 5.32 % | 4.90 % | 4.60 % |
| Purchases | | 34.77 % | 34.69 % | 34.69 % | 35.28 % | 35.32 % |
| Production Costs | | 21.21 % | 21.02 % | 19.58 % | 19.03 % | 20.34 % |
| Closing Stock | | 5.03 % | 5.23 % | 5.67 % | 5.08 % | 5.06 % |
| Depreciation Direct | | .38 % | .37 % | .31 % | .29 % | .29 % |
| **COST OF SALES TOTAL** | | 56.17 % | 55.75 % | 54.23 % | 54.42 % | 55.48 % |
| **GROSS PROFIT** | | 43.84 % | 44.25 % | 45.77 % | 45.58 % | 44.52 % |
| Distribution Costs | | 5.34 % | 4.26 % | 4.57 % | 5.41 % | 4.79 % |
| Depreciation Direct | | .25 % | .25 % | .25 % | .25 % | .25 % |
| **CONTRIBUTION** | | 38.24 % | 39.74 % | 40.95 % | 39.92 % | 39.48 % |
| Overheads | | 31.38 % | 33.16 % | 37.27 % | 35.21 % | 35.62 % |
| Depreciation Indirect | | .53 % | .55 % | .60 % | .57 % | .51 % |
| **OVERHEADS TOTAL** | | 31.91 % | 33.71 % | 37.88 % | 35.77 % | 36.13 % |
| Other Operating Income | | .00 % | .00 % | .00 % | .00 % | .00 % |
| **OPERATING PROFIT** | | 6.34 % | 6.03 % | 3.07 % | 4.15 % | 3.35 % |
| Other Income | | .94 % | .49 % | .29 % | .09 % | .00 % |
| Other Charges | | .00 % | .79 % | .00 % | .24 % | 1.73 % |
| **PROFIT BEFORE INT+TAX** | | 7.28 % | 5.73 % | 3.37 % | 4.01 % | 1.62 % |
| Interest Receivable | | .47 % | .35 % | .28 % | .13 % | .00 % |
| Interest Payable | | .49 % | .66 % | .92 % | 1.04 % | .46 % |
| **PROFIT BEFORE TAXATION** | | 7.26 % | 5.42 % | 2.73 % | 3.10 % | 1.16 % |
| Taxation | | 1.60 % | 1.08 % | .55 % | .62 % | .12 % |
| **PROFIT AFTER TAXATION** | | 5.67 % | 4.34 % | 2.18 % | 2.48 % | 1.04 % |
| Minority Interests | | .57 % | .43 % | .22 % | .25 % | .10 % |
| **PROF BEFORE EXT.ITEMS** | | 5.10 % | 3.90 % | 1.97 % | 2.23 % | .94 % |
| Extraordinary Gain | | 1.03 % | .00 % | .00 % | .00 % | .00 % |
| Extraordinary Loss | | .00 % | .00 % | .00 % | 1.35 % | .00 % |
| **PROF DUE TO PARENT CO.** | | 6.13 % | 3.90 % | 1.97 % | .88 % | .94 % |
| DIVIDENDS Ordinary | | .34 % | .31 % | .13 % | .08 % | .03 % |
| DIVIDENDS Preference | | .03 % | .04 % | .04 % | .04 % | .00 % |
| **RETAINED PROFIT FOR YR** | | 5.75 % | 3.55 % | 1.79 % | .76 % | .91 % |
| RETAINED PROFIT B/Fwd | | 7.93 % | 5.02 % | 4.02 % | 1.40 % | .54 % |
| OTHER Reserve Movement | | .00 % | .00 % | .00 % | 1.68 % | .00 % |
| **RETAINED PROFIT C/Fwd** | | 13.68 % | 8.57 % | 5.81 % | 3.84 % | 1.45 % |

## CASHFLOW ANALYSIS OUTPUT: DETAILED CASHFLOW

CFDEMO
1.05.97
15:43:26

| Files | | | | |
|---|---|---|---|---|
| Current Yr P&L : | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 |
| Current Yr B/S : | Bsdemo5 | Bsdemo4 | Bsdemo3 | Bsdemo2 |
| Current Yr AD : | Addemo5 | Addemo4 | Addemo3 | Addemo2 |
| Prior Yr B/S : | Bsdemo4 | Bsdemo3 | Bsdemo2 | Bsdemo1 |
| Prior Yr AD : | Addemo4 | Addemo3 | Addemo2 | Addemo1 |

| | | | | |
|---|---|---|---|---|
| **FROM OPERATING ACTIVITIES** | | | | |
| Operating profit/(loss) | 185090 | 163078 | 71756 | 101446 |
| Dep'n of tangible fxd assets | 33852 | 31711 | 27025 | 27022 |
| Amortisation of intangibles | 11725 | 0 | 0 | 0 |
| Dimunition of fxd asset invstmnts | 0 | 0 | 0 | 0 |
| (P)/L sale of fxd asset: tangible | -2000 | 0 | 2000 | 0 |
| (P)/L sale of fxd asset: intangible | 0 | 0 | 0 | 0 |
| (P)/L sale of fxd asset: invstmnts | 10000 | 0 | 0 | 0 |
| (P)/L sale of cur asset: invstmnts | 0 | 0 | 0 | 0 |
| (Inc)/dec in stock | -5672 | -9064 | -7961 | -4446 |
| (Inc)/dec in trade debtors | 483 | 8754 | 20216 | 21327 |
| (Inc)/dec in other debtors | -8184 | 31388 | -6442 | -12263 |
| (Inc)/dec in sums due from grp co's | -39242 | -1889 | 25217 | -2605 |
| Inc/(dec) in trade creditors | 8709 | -12232 | 1996 | -56666 |
| Inc/(dec) in other creditors | 31809 | -1970 | 46778 | -92400 |
| **Sub Total** | 226570 | 209776 | 180585 | -18585 |
| **INVESTMENT RETURNS & SVC'G FINANCE** | | | | |
| Interest received | 13761 | 9487 | 6539 | 3251 |
| Interest paid | -14286 | -17914 | -21439 | -25467 |
| Preference dividend paid | -1000 | -1000 | -1000 | -500 |
| **Sub Total** | -1525 | -9427 | -15900 | -22716 |
| **TAXATION (PAID)/REPAID** | -30050 | -17301 | -12747 | -2886 |
| **CAPITAL EXP & FINANCIAL INVESTMENT** | | | | |
| Purchase of FA: tangible | -50164 | -35628 | -5008 | -19976 |
| Purchase of FA: intangible | -81725 | 0 | 0 | 0 |
| Purchase of FA: investments | -100000 | -90000 | -40000 | -22400 |
| Proceeds on sale of FA: tangible | 6000 | 0 | 3000 | 0 |
| Proceeds on sale of FA: intangible | 0 | 0 | 0 | 0 |
| Proceeds on sale of FA: investments | 40000 | 0 | 0 | 0 |
| **Sub Total** | -185889 | -125628 | -42008 | -42376 |
| **OTHER MOVEMENTS** | | | | |
| Net proceeds/(cost) of Ext.Items | 30000 | 0 | 0 | -32985 |
| Non operating income received | 27594 | 13217 | 6874 | 2241 |
| Non operating charges paid | 0 | -21359 | 0 | -5747 |
| Non P&L movement in MI | 0 | 0 | 0 | 0 |
| Non P&L movement in reserves | 0 | 0 | 0 | 0 |
| **Sub Total** | 57594 | -8142 | 6874 | -36491 |
| **EQUITY DIVIDEND PAID** | -8500 | -7000 | -2400 | -1200 |
| **Cash inflow/(outflow) before use of liquid resources & financing** | 58200 | 42278 | 114404 | -124254 |
| **MANAGEMENT OF LIQUID RESOURCES** | | | | |
| (Purchase)/Sale of CA Investments | 20000 | -20000 | -10000 | 0 |
| **FINANCING** | | | | |
| Issue of shares | 0 | 60000 | 0 | 25000 |
| Repurchase of shares | 0 | 0 | 0 | 0 |
| Debt due within 1 year | 0 | 0 | 0 | 50400 |
| Debt due after 1 year | -50400 | -50400 | -50400 | 201600 |
| **Sub Total** | -50400 | 9600 | -50400 | 277000 |
| **CASH INFLOW/(OUTFLOW) IN PERIOD** | 27800 | 31878 | 54004 | 152746 |

## CASHFLOW ANALYSIS OUTPUT: SUMMARY CASHFLOW AND RECONCILIATIONS

CFDEMO
1.05.97
15:43:26

| Files | | | | |
|---|---|---|---|---|
| Current Yr P&L : | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 |
| Current Yr B/S : | Bsdemo5 | Bsdemo4 | Bsdemo3 | Bsdemo2 |
| Current Yr AD : | Addemo5 | Addemo4 | Addemo3 | Addemo2 |
| Prior Yr B/S : | Bsdemo4 | Bsdemo3 | Bsdemo2 | Bsdemo1 |
| Prior Yr AD : | Addemo4 | Addemo3 | Addemo2 | Addemo1 |

**SUMMARY CASHFLOW**

| | | | | |
|---|---|---|---|---|
| FROM OPERATING ACTIVITIES | 226570 | 209776 | 180585 | -18585 |
| INVESTMENT RETURNS & SVC'G FINANCE | -1525 | -9427 | -15900 | -22716 |
| TAXATION (PAID)/REPAID | -30050 | -17301 | -12747 | -2886 |
| CAPITAL EXP & FINANCIAL INVESTMENT | -185889 | -125628 | -42008 | -42376 |
| OTHER MOVEMENTS | 57594 | -8142 | 6874 | -36491 |
| EQUITY DIVIDEND PAID | -8500 | -7000 | -2400 | -1200 |
| CASH INFLOW/(OUTFLOW) BEFORE USE OF LIQUID RESOURCES & FINANCING | 58200 | 42278 | 114404 | -124254 |
| MANAGEMENT OF LIQUID RESOURCES | 20000 | -20000 | -10000 | 0 |
| FINANCING | -50400 | 9600 | -50400 | 277000 |
| **CASH INFLOW/(OUTFLOW) IN PERIOD** | 27800 | 31878 | 54004 | 152746 |

**RECON NET C/FLW TO NET FUNDS/(DEBT)**

| | | | | |
|---|---|---|---|---|
| Cash inflow/(outflow) in the period | 27800 | 31878 | 54004 | 152746 |
| Cash inflow/(outflow) from debt | 50400 | 50400 | 50400 | -252000 |
| Cash inflow/(outflow) from lqd rscs | -20000 | 20000 | 10000 | 0 |
| **Movement in Net funds/(debt)** | 58200 | 102278 | 114404 | -99254 |
| **Net funds/(debt) at start of period** | 23368 | -78910 | -193314 | -94060 |
| **Net funds/(debt) at end of period** | 81568 | 23368 | -78910 | -193314 |

**RECON OF PERIOD END BALANCE**

| | | | | |
|---|---|---|---|---|
| Cash at bank and in hand | 172368 | 144568 | 112690 | 58686 |
| Overdraft | 0 | 0 | 0 | 0 |
| Debt > 1 year | -50400 | -100800 | -151200 | -201600 |
| Debt < 1 year | -50400 | -50400 | -50400 | -50400 |
| CA investments | 10000 | 30000 | 10000 | 0 |
| **As above** | 81568 | 23368 | -78910 | -193314 |

# INPUT UPON WHICH EXAMPLES ARE BASED: PROFIT & LOSS

| PROFIT & LOSS INPUT | Pldemo5 | Pldemo4 | Pldemo3 | Pldemo2 | Pldemo1 |
|---|---|---|---|---|---|
| **TURNOVER TOTAL** | 2920531 | 2703434 | 2334844 | 2445435 | 2368734 |
| **COST OF SALES** | | | | | |
| Opening Stock | 141349 | 132285 | 124324 | 119878 | 108901 |
| Purchases | 1015537 | 937733 | 809877 | 862784 | 836577 |
| Production Costs | 619321 | 568377 | 457121 | 465437 | 481791 |
| Closing Stock | 147021 | 141349 | 132285 | 124324 | 119878 |
| Depreciation Direct | 11130 | 10004 | 7127 | 7007 | 6780 |
| **COST OF SALES TOTAL** | 1640316 | 1507050 | 1266164 | 1330782 | 1314171 |
| **GROSS PROFIT** | 1280215 | 1196384 | 1068680 | 1114653 | 1054563 |
| Distribution Costs | 156027 | 115172 | 106742 | 132272 | 113437 |
| Depreciation Direct | 7301 | 6759 | 5837 | 6114 | 5922 |
| **CONTRIBUTION** | 1116887 | 1074453 | 956101 | 976267 | 935204 |
| Overheads | 916376 | 896427 | 870284 | 860920 | 843841 |
| Depreciation Indirect | 15421 | 14948 | 14061 | 13901 | 12097 |
| **OVERHEADS TOTAL** | 931797 | 911375 | 884345 | 874821 | 855938 |
| Other Operating Income | 0 | 0 | 0 | 0 | 0 |
| **OPERATING PROFIT** | 185090 | 163078 | 71756 | 101446 | 79266 |
| Other Income | 27594 | 13217 | 6874 | 2241 | 0 |
| Other Charges | 0 | 21359 | 0 | 5747 | 40981 |
| **PROFIT BEFORE INT+TAX** | 212684 | 154936 | 78630 | 97940 | 38285 |
| Interest Receivable | 13761 | 9487 | 6539 | 3251 | 0 |
| Interest Payable | 14286 | 17914 | 21439 | 25467 | 10871 |
| **PROFIT BEFORE TAXATION** | 212159 | 146509 | 63730 | 75724 | 27414 |
| Taxation | 46675 | 29301 | 12747 | 15145 | 2741 |
| **PROFIT AFTER TAXATION** | 165484 | 117208 | 50983 | 60579 | 24673 |
| Minority Interests | 16548 | 11721 | 5098 | 6058 | 2467 |
| **PROF BEFORE EXT.ITEMS** | 148936 | 105487 | 45885 | 54521 | 22206 |
| Extraordinary Gain | 30000 | 0 | 0 | 0 | 0 |
| Extraordinary Loss | 0 | 0 | 0 | 32985 | 0 |
| **PROF DUE TO PARENT CO.** | 178936 | 105487 | 45885 | 21536 | 22206 |
| DIVIDENDS Ordinary | 10000 | 8500 | 3000 | 2000 | 600 |
| DIVIDENDS Preference | 1000 | 1000 | 1000 | 1000 | 0 |
| **RETAINED PROFIT FOR YR** | 167936 | 95987 | 41885 | 18536 | 21606 |
| RETAINED PROFIT B/Fwd | 231714 | 135727 | 93842 | 34281 | 12675 |
| OTHER Reserve Movement | 0 | 0 | 0 | 41025 | 0 |
| **RETAINED PROFIT C/Fwd** | 399650 | 231714 | 135727 | 93842 | 34281 |

## INPUT UPON WHICH EXAMPLES ARE BASED: BALANCE SHEET

| BALANCE SHEET INPUT | Bsdemo5 | Bsdemo4 | Bsdemo3 | Bsdemo2 | Bsdemo1 |
|---|---|---|---|---|---|
| **FIXED ASSETS** | | | | | |
| Tangible: Cost | 306541 | 264377 | 228749 | 228741 | 208765 |
| Tangible: Acc Dep'n | 160409 | 130557 | 98846 | 71821 | 44799 |
| Tangible: Net Book Val | 146132 | 133820 | 129903 | 156920 | 163966 |
| Intangible | 93450 | 23450 | 23450 | 23450 | 23450 |
| Investments | 203400 | 153400 | 63400 | 23400 | 1000 |
| **TOTAL FIXED ASSETS** | 442982 | 310670 | 216753 | 203770 | 188416 |
| **CURRENT ASSETS** | | | | | |
| Stocks | 147021 | 141349 | 132285 | 124324 | 119878 |
| Trade Debtors | 302021 | 302504 | 311258 | 331474 | 352801 |
| Other Debtors | 67350 | 48791 | 69804 | 56837 | 44249 |
| Cur.Asset Investments | 10000 | 30000 | 10000 | 0 | 0 |
| Cash at Bank & In Hand | 172368 | 144568 | 112690 | 58686 | 0 |
| **TOTAL CURRENT ASSETS** | 698760 | 667212 | 636037 | 571321 | 516928 |
| **CREDITORS DUE < 1 YEAR** | | | | | |
| Interest Bearing Loans | 50400 | 50400 | 50400 | 50400 | 0 |
| Bank Overdraft | 0 | 0 | 0 | 0 | 94060 |
| Trade Creditors | 129461 | 120752 | 132984 | 130988 | 187654 |
| Other Creditors | 268956 | 247889 | 227873 | 148753 | 179874 |
| **TOTAL CURRENT LIABIL'S** | 448817 | 419041 | 411257 | 330141 | 461588 |
| **NET CURRENT ASSETS** | 249943 | 248171 | 224780 | 241180 | 55340 |
| **TOTAL ASSETS LESS CURRENT LIABILITIES** | 692925 | 558841 | 441533 | 444950 | 243756 |
| **CREDITORS DUE > 1 YEAR** | | | | | |
| Interest Bearing Loans | 50400 | 100800 | 151200 | 201600 | 0 |
| Other Creditors | 100000 | 100000 | 100000 | 100000 | 100000 |
| **TOTAL LONG TERM CRED'S** | 150400 | 200800 | 251200 | 301600 | 100000 |
| **PVSN: LIABIL'S+CHARGES** | 0 | 0 | 0 | 0 | 50000 |
| **ACC'LS & DEF'D INCOME** | 0 | 0 | 0 | 0 | 0 |
| **NET ASSETS** | 542525 | 358041 | 190333 | 143350 | 93756 |
| **SHARE CPTL & RESERVES** | | | | | |
| Ordinary Shares | 50000 | 50000 | 20000 | 20000 | 10000 |
| Preference Shares | 10000 | 10000 | 10000 | 10000 | 0 |
| Share Premium Account | 35000 | 35000 | 5000 | 5000 | 0 |
| Revaluation Reserve | 0 | 0 | 0 | 0 | 0 |
| Other Reserves | 0 | 0 | 0 | 0 | 41025 |
| Profit & Loss Account | 399650 | 231714 | 135727 | 93842 | 34281 |
| **SHAREHOLDERS FUNDS** | 494650 | 326714 | 170727 | 128842 | 85306 |
| Minority Interest | 47875 | 31327 | 19606 | 14508 | 8450 |
| **NET ASSETS** | 542525 | 358041 | 190333 | 143350 | 93756 |

# INPUT UPON WHICH EXAMPLES ARE BASED: ADDITIONAL DATA

| ADDITIONAL DATA INPUT | Addemo5 | Addemo4 | Addemo3 | Addemo2 | Addemo1 |
|---|---|---|---|---|---|
| **USED FOR RATIO ANALYSIS** | | | | | |
| **ORDINARY SHARES** | | | | | |
| Number Issued | 50000 | 40000 | 20000 | 15000 | 10000 |
| Market Price (Pence) | 218 | 200 | 175 | 150 | 75 |
| **EMPLOYEE DETAILS** | | | | | |
| Av. Number Full Time | 30 | 28 | 30 | 29 | 30 |
| Total Wages & Salaries | 738211 | 675165 | 675147 | 627488 | 581502 |
| **USED FOR CASHFLOW ANALYSIS** | | | | | |
| **PROFIT & LOSS ITEMS** | | | | | |
| P/L sale FA: tangible | 2000 | 0 | (2000) | 0 | 0 |
| P/L sale FA: intangible | 0 | 0 | 0 | 0 | 0 |
| Amortisation of " | 11725 | 0 | 0 | 0 | 0 |
| P/L FA investments | (10000) | 0 | 0 | 0 | 0 |
| Dimunition FA " | 0 | 0 | 0 | 0 | 0 |
| P/L CA investments | 0 | 0 | 0 | 0 | 0 |
| **INCL' IN FXD ASSETS** | | | | | |
| Addt's FA: tangible | 50164 | 35628 | 5008 | 19976 | 40000 |
| Addt's FA: intangible | 81725 | 0 | 0 | 0 | 23450 |
| Addt's FA: investments | 100000 | 90000 | 40000 | 22400 | 1000 |
| **INCL' IN OTHER DEBTORS** | | | | | |
| CorpTax (incl ACT) Dbtr | 1375 | 1000 | 625 | 475 | 150 |
| Bal's with group Co's | 26375 | 16375 | 6375 | 0 | 0 |
| **INCL' IN OTHER CRDTRS** | | | | | |
| CorpTax (incl ACT) Cdtr | 45000 | 28000 | 15625 | 15475 | 2891 |
| Pref Dividend payable | 500 | 500 | 500 | 500 | 0 |
| Ordinary " " | 5000 | 3500 | 2000 | 1400 | 600 |
| Bal's with group Co's | 132856 | 162098 | 153987 | 122395 | 125000 |
| **INCL' PVSN LIAB/CHGS** | | | | | |
| Deferred Taxation | 0 | 0 | 0 | 0 | 0 |
| **MOVEMENT IN SHARE CPTL** | | | | | |
| New share issues: cost | 0 | 60000 | 0 | 25000 | 0 |

## Appendix G – The Processed Data

The following pages are the sample of the fully processed data typical for each network. Model A or Model B must access 415,012 data items before making a prediction for the particular company. It is difficult to print the entire data records because it will run into 322 pages, however, 20 pages are shown here as sample. Full data records can found on the CD-ROM enclosed with this thesis.

Recall that neural networks do not recognised symbolic data. The training set must be processed in a format suitable for neural network inputs.

| I@Tm | Pbt | Dvd | Shf | Prt | Rce | Tm | Csa | Grp | Dpn | Oxp | Opl | Ocm | Rsv | Cap | Dab | Wcp | Nla | Ctx | Ovd | Dts | Cts | Tou | Cnr | Lqr | Sol | Asc | Gm | Pmm | Rsh | Rce | Rta | Icv |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.9839 | -0.8457 | 0.9718 | -0.9408 | -0.5854 | 0.2198 | -0.9845 | 0.9394 | -0.9544 | -0.9824 | 0.9700 | -0.8465 | -0.9866 | -0.9609 | -0.9803 | 0.9953 | -0.9805 | -0.9489 | 0.9679 | 0.9568 | -0.5924 | 0.7280 | -0.9762 | -0.9100 | -0.9708 | -0.2517 | -0.9282 | -0.6809 | 0.3495 | -0.1713 | -0.0269 | 0.3989 | -0.8014 |
| -0.9562 | -0.8735 | 0.9768 | -0.9382 | -0.7187 | 0.0795 | -0.9580 | 0.8741 | -0.9074 | -0.9883 | 0.9584 | -0.8794 | -0.9684 | -0.9631 | -0.9585 | 0.9838 | -0.9766 | -0.9313 | 0.9667 | 0.9605 | -0.5750 | 0.7104 | -0.9747 | -0.8495 | -0.9708 | -0.3230 | -0.9672 | -0.8711 | 0.2587 | -0.2781 | -0.1431 | 0.1100 | -0.8384 |
| -0.9961 | -0.8525 | 0.9755 | -0.9502 | -0.5854 | 0.2031 | -0.9983 | 0.9596 | -0.9771 | -0.9997 | 0.9676 | -0.8374 | -0.9865 | -0.9668 | -0.9917 | 0.9901 | -0.9842 | -0.9339 | 0.9702 | 0.9589 | -0.5966 | 0.7358 | -0.9784 | -0.5794 | -0.9813 | -0.2892 | -0.9838 | -0.8521 | 0.3089 | -0.1729 | -0.0409 | 0.3732 | -0.8244 |
| -0.8097 | 1.0000 | -0.9265 | -0.8593 | 1.0000 | 0.1792 | 1.0000 | 0.4545 | -0.9758 | 1.0000 | -1.0000 | -1.0000 | 1.0000 | 1.0000 | 1.0000 | 0.9838 | 1.0000 | -0.9489 | -1.0000 | -0.6817 | -0.5924 | 0.7290 | 1.0000 | -0.9637 | -0.9610 | -0.5136 | -0.9836 | -0.7083 | 0.3205 | -0.2010 | -0.0805 | 0.2512 | -0.8296 |
| -0.9852 | -0.8409 | 0.9725 | -0.9461 | -0.5854 | 0.1948 | -0.9858 | 0.8741 | -0.9685 | -0.9723 | 0.9694 | -0.8504 | -0.9871 | -0.9655 | -0.9810 | 0.9880 | -0.9788 | -0.9412 | 0.9712 | 0.9629 | -0.5847 | 0.7310 | -0.9746 | -0.9125 | -0.9729 | -0.3833 | -0.9801 | -0.8262 | 0.3371 | -0.1880 | -0.0476 | 0.3350 | -0.8251 |
| -0.9993 | -0.8598 | 0.9168 | -0.9443 | -0.6192 | 0.1413 | -0.9993 | 0.9596 | -0.9758 | -0.9996 | 0.9676 | -0.8374 | -0.9865 | -0.9632 | -0.9898 | 0.9887 | -0.9829 | -0.9499 | 0.9694 | 0.9586 | -0.5947 | 0.7303 | -0.9762 | -0.9035 | -0.9729 | -0.1984 | -0.9836 | -0.7009 | 0.0385 | -0.2325 | -0.0819 | 0.2016 | -0.8325 |
| -0.8111 | -0.7715 | 0.9211 | -0.7739 | 1.0000 | 0.1974 | -0.8190 | 0.3793 | -0.8436 | -0.9966 | 0.9671 | -0.8490 | -0.9763 | -0.8629 | -0.9082 | 0.9845 | -0.9011 | -0.6515 | 0.9063 | 0.9080 | -0.5718 | 0.6481 | -0.9134 | -0.7003 | -0.9773 | -0.2803 | -0.9556 | -0.6973 | 0.3282 | -0.1881 | -0.0455 | 0.3381 | -0.8202 |
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| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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| -0.9762 | -0.6668 | 0.8723 | -0.4181 | -0.4787 | 0.1908 | -0.9672 | 0.9851 | -0.9416 | -0.9763 | 0.9697 | -0.8418 | -0.9877 | -0.9574 | -0.9975 | 0.9958 | -0.9831 | -0.9491 | 0.9725 | 0.9651 | -0.5968 | 0.7371 | -0.9755 | -0.8585 | -0.9601 | -0.3859 | -0.9914 | -0.7293 | 0.3699 | 0.0249 | 0.2367 | 0.6807 | 0.7487 |
| -0.9678 | -0.8567 | 0.9733 | -0.9103 | -0.6057 | 0.2985 | -0.9819 | -0.1439 | -0.8738 | -0.9998 | 0.9699 | -0.8475 | -0.9874 | -0.9670 | -0.9950 | 0.9959 | -0.9827 | -0.9509 | 0.9617 | 0.9518 | -0.5958 | 0.7315 | -0.9799 | -0.7775 | -0.9454 | -0.2372 | -0.9949 | -0.6698 | 0.3868 | -0.2136 | -0.0753 | 0.2673 | -0.8280 |
| -0.9876 | -0.8487 | 0.9575 | -0.8921 | -0.6277 | 0.2155 | -0.9319 | 0.8877 | -0.9512 | -0.9878 | 0.9612 | -0.5882 | -0.9877 | -0.9418 | -0.9846 | 0.9523 | -0.9679 | -0.9495 | 0.9666 | 0.9559 | -0.5968 | 0.7367 | -0.9574 | -0.8161 | -0.9533 | -0.0961 | -0.9925 | -0.7002 | 0.6265 | -0.1161 | 0.0568 | 0.7359 | -0.5393 |
| -0.9105 | -0.7664 | 0.9708 | -0.8548 | -0.5783 | 0.2012 | -0.9996 | 0.7728 | -0.9806 | -0.9932 | 0.9655 | -0.8354 | -0.9877 | -0.9437 | -0.8733 | 0.9959 | -0.9688 | -0.9525 | 0.9339 | 0.9220 | -0.5971 | 0.7283 | -0.9618 | -0.8675 | -0.9678 | -0.3855 | -0.9851 | -0.8906 | 0.3345 | -0.1064 | 0.0382 | 0.4385 | -0.8079 |
| -0.9819 | -0.8589 | 0.9733 | -0.9538 | -0.6248 | 0.1259 | -0.9939 | 0.8034 | -0.9614 | 0.4932 | 1.0000 | -0.2309 | -0.1569 | -0.9646 | -0.9875 | 0.9917 | -0.9786 | -0.9354 | 0.9503 | 0.9606 | -0.5723 | 0.7144 | -0.9774 | -0.7968 | -0.9489 | -0.1912 | -0.9906 | -0.7305 | 0.5044 | -0.0435 | 0.1520 | 0.9025 | -0.8053 |
| -0.9981 | -0.8550 | 0.9663 | -0.9535 | -0.6299 | 0.3672 | -0.9937 | 0.9851 | -0.9707 | -0.7122 | 0.8848 | -0.4843 | -0.9238 | -0.9591 | -0.9910 | 0.9959 | -0.9808 | -0.9467 | 0.9368 | 0.9351 | -0.5886 | 0.7298 | -0.9759 | -0.7723 | -0.9559 | -0.2686 | -0.9840 | -0.6932 | 0.3519 | -0.1645 | -0.0236 | 0.4082 | -0.8024 |

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| Slt | Dto | Nto | Sto | Pps | Cto | Wps | Sr | Tps | Rsv | Opi | Ctx | Ovd | Deb | Dps | Crs | Lon | Ovd | Rsv | Ar | Lir | Bbr | Ibr | Emp | Ecm | Desired Output |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.7615 | -0.9388 | -0.6112 | -0.8950 | -0.5739 | -0.8966 | -0.4187 | -0.9649 | -0.9894 | -0.9594 | -0.8465 | 0.9834 | 0.9867 | -0.9898 | -0.5390 | -0.1527 | 0.9541 | 0.9725 | -0.9783 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9679 | -0.9643 | -0.4822 | -0.8259 | -0.6152 | -0.8887 | -0.3659 | -0.9653 | -0.9900 | -0.9616 | -0.8794 | 0.9887 | 0.9982 | -0.9543 | -0.5478 | -0.1514 | 1.0000 | 0.9511 | -0.8155 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9979 | -0.8791 | -0.6875 | -0.5345 | -0.4141 | -0.8710 | 0.9246 | -0.9739 | -0.9011 | -0.9854 | -0.8374 | 0.9857 | 0.9978 | -0.9736 | -0.5474 | -0.1526 | 0.9838 | 0.9772 | -0.9819 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9751 | -0.9861 | -0.2947 | -0.9572 | -0.5681 | -0.8514 | -0.3050 | -0.9687 | -0.7332 | 1.0000 | -1.0000 | 0.2724 | 0.4240 | -0.9741 | -0.5478 | -0.1520 | 0.9457 | 0.5191 | -0.7104 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9290 | -0.9786 | -0.6331 | -0.9244 | -0.5837 | -0.9111 | -0.3896 | -0.9763 | -0.9899 | -0.9640 | -0.8504 | 0.9857 | 0.9969 | -0.9629 | -0.5469 | -0.1554 | 0.9533 | 0.9779 | -0.9727 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9896 | -0.9947 | -0.7030 | -0.6476 | -0.9136 | 0.9584 | -0.8704 | -0.9716 | -0.4717 | -0.9617 | -0.8374 | 0.9861 | 0.9982 | -0.9719 | -0.5472 | -0.1522 | 0.9537 | 0.9784 | -0.9651 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9941 | -0.8654 | -0.6053 | -0.7099 | -0.5572 | -0.9173 | -0.0744 | -0.9656 | -0.9709 | -0.9615 | -0.8490 | 0.9766 | 0.9814 | -0.9515 | -0.5016 | -0.1503 | 0.9794 | 0.9625 | -0.9799 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9709 | -0.9607 | -0.6176 | -0.7077 | -0.5666 | -0.8981 | -0.4805 | -0.9607 | -0.9886 | -0.9660 | -0.6954 | 0.9721 | 0.9881 | -0.8940 | -0.5478 | -0.4040 | 0.9539 | 0.9704 | -0.9786 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9461 | -0.7141 | -0.8657 | -0.8270 | -0.5562 | -0.9914 | -0.3887 | -0.9784 | -0.9670 | 1.0000 | -1.0000 | -0.4005 | -0.4444 | -0.4296 | -0.5478 | -0.1503 | 0.9536 | 1.0000 | -0.9793 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9686 | -0.9678 | -0.5858 | -0.8939 | -0.5991 | -0.8519 | -0.3900 | -0.9760 | -0.9918 | -0.8720 | -0.9519 | 0.9521 | 0.9840 | -0.6442 | -0.3706 | -0.1542 | 0.9529 | 0.8232 | -0.9797 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9082 | -0.9801 | 1.0000 | -0.9152 | -0.6147 | -0.5048 | -0.4502 | -0.9753 | -0.9846 | -0.9694 | -0.8389 | 0.9840 | 0.9981 | -0.9602 | -0.5478 | -0.1571 | 0.9538 | 0.9777 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9639 | -0.9743 | -0.5000 | -0.9480 | -0.5903 | -0.8766 | -0.4001 | -0.8876 | -0.9870 | -0.9622 | -0.8448 | 0.9859 | 0.9982 | -0.9676 | -0.5478 | -0.1506 | 0.9526 | 0.9768 | -0.9789 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9284 | -0.9642 | -1.0000 | -0.9512 | -0.6267 | -0.9285 | -0.4064 | -0.9963 | -0.9874 | -0.9734 | -0.8832 | 0.9855 | 0.9847 | -0.9741 | -0.5416 | -0.1550 | 0.9584 | 0.9741 | -0.9787 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9931 | -0.9935 | -0.5775 | -0.7481 | -0.5038 | -0.9286 | -0.1437 | -0.9428 | -0.9788 | -0.9300 | -0.6743 | 0.9717 | 0.9801 | -0.9687 | -0.4736 | -0.2613 | 0.5190 | 0.9625 | -0.9784 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9954 | -0.8498 | -0.6503 | -0.6430 | -0.4870 | -0.7618 | 0.0031 | -0.9517 | -0.9494 | -0.9043 | -0.8504 | 0.9857 | 0.9982 | -0.9735 | -0.5383 | -0.1512 | 0.9538 | 0.9688 | -0.9790 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9898 | -0.9046 | -0.6225 | -0.4004 | -0.5937 | -0.9159 | -0.0263 | -0.9054 | -0.9446 | -0.9694 | -0.9374 | 0.9857 | 0.9982 | -0.9738 | -0.5475 | -0.1503 | 0.9529 | 0.9773 | -0.9842 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9844 | -0.5401 | -0.5876 | 1.0000 | -0.5499 | -0.9784 | -0.5098 | -0.9789 | -0.6973 | -0.9740 | -0.8490 | 0.9856 | 0.9973 | -0.9660 | -0.5478 | -0.1530 | 0.9538 | 0.9790 | -0.9878 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9680 | -0.9761 | -0.5047 | -0.9434 | -0.5857 | -0.8241 | -0.4010 | -0.9329 | -0.9959 | -0.9668 | -0.6954 | 0.9864 | 0.9970 | -0.9655 | -0.5390 | -0.4020 | 0.9528 | 0.9730 | -0.9757 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.8927 | -0.9897 | -0.5030 | -0.9285 | -0.5949 | -0.8962 | -0.4047 | -0.9603 | -0.9958 | -0.9650 | -0.6954 | 0.9837 | 0.9962 | -0.9703 | -0.5390 | -0.1555 | 0.9526 | 0.9529 | -0.9826 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9612 | -0.8418 | -0.6527 | -0.8869 | -0.5899 | -0.9115 | -0.4065 | -0.9731 | -0.9856 | -0.9387 | -0.9522 | 0.9853 | 0.9978 | -0.9740 | -0.5468 | -0.1561 | 0.9594 | 0.9559 | -0.9736 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| 0.0395 | -0.9314 | -0.6982 | -0.9618 | -0.5747 | -0.6437 | -0.4259 | -0.9683 | -0.9894 | -0.9661 | -0.8481 | 0.9645 | 0.9982 | -0.9425 | -0.5393 | -0.1534 | 0.5190 | 0.9790 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9863 | -0.9828 | -0.8586 | -0.8350 | -0.6271 | -0.6032 | -0.3591 | -0.9371 | -0.9712 | -0.9498 | -0.8720 | 0.9721 | 0.9881 | -0.8940 | -0.4662 | -0.1550 | 0.9467 | 0.9722 | -0.9784 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9922 | -0.9830 | -0.6485 | -0.3277 | -0.4381 | -0.9799 | 0.5820 | -0.4767 | -0.9072 | -0.9697 | -0.8465 | 0.9776 | 0.9910 | -0.9394 | -0.5350 | -0.1563 | 0.9538 | 0.9581 | -0.9794 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9692 | -0.9579 | -0.5663 | -0.9141 | -0.5835 | -0.9068 | -0.3919 | -0.8746 | -0.9942 | -0.9394 | -0.6579 | 0.9848 | 0.9970 | -0.9740 | -0.5478 | -0.1652 | 0.8347 | 0.7292 | -0.9794 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.8122 | -0.9082 | -0.7047 | -0.9912 | -0.5821 | -0.9523 | -0.4171 | -0.3178 | -0.9880 | -0.9533 | -0.8524 | 0.9770 | 0.9923 | -0.9580 | -0.5272 | -0.1567 | 0.9523 | 0.9789 | -0.9770 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9673 | -0.9711 | -0.6278 | -0.8890 | -0.5417 | -0.8843 | -0.3795 | -0.9706 | -0.9885 | -0.9498 | -0.8465 | 0.9860 | 0.9982 | -0.9711 | -0.5424 | -0.1503 | 0.9526 | 0.9798 | -0.9768 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9820 | -0.9694 | -0.6260 | -0.7279 | -0.5653 | -0.9490 | -0.2408 | -0.8190 | -0.9771 | -0.9679 | -0.8374 | 0.9746 | 0.9920 | -0.9672 | -0.5336 | -0.1510 | 0.9595 | 0.9771 | -0.9793 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9459 | -0.9309 | -0.5799 | -0.8129 | -0.4851 | -0.9576 | -0.3795 | -0.8955 | -0.9866 | -0.9580 | -0.7906 | 0.9858 | 0.9982 | -0.9716 | -0.5478 | -0.1570 | 0.9467 | 0.9638 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9549 | -0.9643 | -0.3722 | -0.9147 | -0.6475 | -0.8477 | -0.4051 | -0.8463 | -0.9934 | -0.9695 | -0.8816 | 0.9854 | 0.9980 | -0.9717 | -0.5478 | -0.2045 | 0.9465 | 0.9775 | -0.9715 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9429 | -0.9791 | -0.5604 | -0.9422 | -0.5879 | -0.8932 | -0.3962 | -0.9611 | -0.9962 | -0.9678 | -0.6954 | 0.9720 | 0.9784 | -0.9720 | -0.5478 | -0.1931 | 0.9498 | 0.9776 | -0.9609 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9985 | -0.9677 | -0.7059 | -0.9151 | -0.1684 | -0.5585 | -0.1377 | -0.9531 | -0.6820 | -0.8019 | -0.8623 | 0.9857 | 0.9982 | -0.9734 | -0.5478 | -0.1529 | 0.9378 | 0.9773 | -0.9753 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9772 | -0.9785 | -0.6627 | -0.9608 | -0.6839 | -0.7313 | -0.4076 | -0.9079 | -0.9881 | -0.9679 | -0.8583 | 0.9832 | 0.9982 | -0.9741 | -0.5478 | -0.1923 | 0.9148 | 0.9776 | -0.9800 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9834 | -0.9600 | -0.4178 | -0.0370 | 1.0000 | -0.9177 | -0.3525 | 1.0000 | -0.9877 | -0.9671 | -0.8465 | 0.9850 | 0.9926 | -0.9708 | -0.5478 | -0.1525 | 0.9522 | 0.9758 | -0.9596 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9820 | -0.9667 | -0.6882 | -0.8271 | -0.5121 | -0.6019 | -0.4248 | -0.9728 | -0.9201 | -0.9519 | -0.8358 | 0.9858 | 0.9982 | -0.9704 | -0.5475 | -0.1647 | 0.9528 | 0.9733 | -0.7785 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.8951 | -0.9533 | -0.2012 | -0.8704 | -0.6855 | -0.9021 | -0.4061 | -0.9757 | -0.9948 | -0.9711 | -0.8734 | 0.9953 | 0.9982 | -0.9111 | -0.5283 | -0.1720 | 0.9379 | 0.9722 | -0.9797 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9352 | -0.9609 | -0.3320 | -0.6934 | -0.6432 | -0.8036 | -0.4216 | -0.9790 | -0.9858 | -0.9656 | -0.6954 | 0.9855 | 0.9963 | -0.9711 | -0.5478 | -0.1591 | 0.9467 | 0.9649 | -0.9142 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9703 | -0.8469 | -0.4609 | -0.8957 | -0.5923 | -0.9391 | -0.3953 | -0.9682 | -0.9849 | -0.9719 | -0.8493 | 0.9789 | 0.9923 | -0.9680 | -0.5368 | -0.1503 | 0.4843 | 0.9557 | -0.9794 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9435 | -0.9594 | -0.6272 | -0.9187 | -0.5353 | -0.9128 | -0.4011 | -0.9363 | -0.9808 | -0.9559 | -0.6954 | 0.9851 | 0.9974 | -0.9685 | -0.5478 | -0.1512 | 0.9465 | 0.9804 | -0.9574 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9730 | -0.9627 | -0.5935 | -0.9015 | -0.5744 | -0.8971 | -0.3835 | -0.9346 | -0.9925 | -0.9630 | -0.8495 | 0.9839 | 0.9958 | -0.9554 | -0.5439 | -0.1689 | 0.9498 | 0.9791 | -0.9089 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.7796 | -0.9718 | 0.5688 | -0.7836 | -0.5751 | -0.8303 | -0.4087 | -0.9762 | -0.9922 | -0.9688 | -0.6954 | 0.6938 | 0.7412 | -0.1088 | -0.1149 | -0.1613 | 0.9378 | 0.8403 | -0.9794 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9475 | -0.9720 | -0.6343 | -0.8719 | -0.5810 | -0.8582 | -0.3904 | -0.9751 | -0.9848 | -0.1253 | -0.8465 | 0.9769 | 0.9811 | -0.9521 | -0.5131 | -0.1600 | 0.9148 | 0.2303 | -0.9798 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9624 | -0.9744 | -0.6550 | -0.9263 | -0.5662 | -0.8608 | -0.3951 | -0.9722 | -0.9895 | -0.9418 | -0.7949 | 0.9602 | 0.9893 | -0.9292 | -0.5061 | -0.1622 | 0.9522 | 0.9711 | -0.9796 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9711 | -0.9674 | -0.6207 | -0.8731 | -0.5453 | -0.9222 | -0.3655 | -0.9711 | -0.9889 | -0.9151 | -0.6954 | 0.9855 | 0.9981 | -0.9725 | -0.5463 | -0.1508 | 0.9498 | 0.8874 | -0.9789 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9694 | -0.9678 | -0.5911 | -0.8347 | -0.5808 | -0.9177 | -0.3525 | 1.0000 | -0.9887 | -0.9674 | -0.8518 | 0.9301 | 0.9899 | -0.5506 | -0.4954 | -0.1526 | 0.9150 | 0.9780 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9520 | -0.9368 | 0.0213 | -0.7436 | -0.5798 | -0.8625 | -0.4040 | -0.9748 | -0.9919 | -0.8969 | -0.6954 | 0.9822 | 0.9959 | -0.9568 | -0.5478 | -0.1595 | 0.9509 | 0.8094 | -0.9733 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9834 | -0.9712 | -0.6047 | -0.8977 | -0.5788 | -0.9358 | -0.3493 | -0.9747 | -0.9900 | -0.9559 | -0.8227 | 0.9858 | 0.9982 | -0.9709 | -0.5478 | -0.1506 | 0.9490 | 0.9577 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.1043 | -0.9607 | -0.3586 | -0.8688 | -0.6415 | -0.8635 | -0.4196 | -0.9762 | -0.9940 | -0.9689 | -0.8623 | 0.6662 | 0.6340 | -0.7201 | -0.5286 | -0.1726 | 0.9512 | 0.9689 | -0.9790 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9839 | -0.9607 | -0.4036 | -0.8891 | -0.5711 | -0.7925 | -0.4109 | -0.9789 | -0.8119 | -0.9143 | 1.0000 | 0.9478 | 0.7508 | 0.0525 | -0.4942 | -0.1522 | 0.9365 | 1.0000 | -0.9376 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
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| -0.9199 | -0.9642 | -0.7006 | -0.9541 | -0.7922 | -0.4510 | -0.4333 | -0.9358 | -0.9602 | -0.9327 | -0.8558 | 0.9844 | 0.9959 | -0.9675 | -0.5473 | -0.1508 | 0.9435 | 0.9710 | -0.9514 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9866 | -0.9497 | -0.5178 | -0.9649 | -0.5976 | -0.8822 | -0.4139 | -0.9696 | -0.9820 | -0.9665 | -0.8445 | 0.9851 | 0.9962 | -0.9543 | -0.5462 | -0.1506 | 0.9443 | 0.9162 | -0.9781 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9807 | -0.9731 | -0.5923 | -0.9626 | -0.5894 | -0.8857 | -0.3441 | -0.9686 | -0.9882 | -0.9582 | -0.8558 | -0.7470 | -0.0709 | 1.0000 | -0.3368 | -0.1507 | 0.9143 | 0.9587 | -0.9252 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9322 | -0.9622 | -0.6166 | -0.3521 | -0.5312 | -0.9695 | -0.3759 | -0.9768 | -0.9414 | 1.0000 | -0.5570 | 0.9739 | 0.9869 | -0.9229 | -0.5480 | -0.1503 | 0.9368 | 0.9780 | -0.9786 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
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| | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.9700 | -0.9689 | -0.6538 | -0.9390 | -0.5884 | -0.8898 | -0.3606 | -0.9661 | -0.9783 | 0.7303 | -0.9558 | -1.0000 | -1.0000 | 0.4478 | -0.4473 | -0.1513 | 0.9490 | 0.8714 | -0.9674 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
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| -0.9674 | -0.9476 | -0.5817 | -0.8798 | -0.5547 | -0.8519 | -0.4217 | -0.9765 | -0.9887 | -0.2089 | -0.8531 | 0.9857 | 0.9880 | -0.9741 | -0.5478 | -0.1520 | 0.9143 | 0.9789 | -0.9815 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9272 | -0.9878 | -0.5467 | -0.8885 | -0.7232 | -0.8331 | -0.4087 | -0.9757 | -0.9907 | -0.9607 | -0.8362 | 0.9833 | 0.9979 | -0.9656 | -0.5478 | -0.4144 | 0.9481 | 0.9709 | -1.0000 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9841 | -0.9728 | -0.2385 | -0.7190 | -0.5236 | -0.8740 | -0.3260 | -0.9680 | -0.9871 | -0.9674 | -0.8512 | 0.9842 | 0.9965 | -0.9595 | -0.5387 | -0.1564 | 0.8756 | 0.9711 | -0.9771 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9847 | -0.9733 | -0.5503 | -0.8428 | -0.5822 | -0.9352 | -0.3015 | -0.9381 | -0.9877 | -0.9593 | -0.7549 | 0.1914 | 0.5687 | 1.0000 | -0.2665 | -0.2856 | 0.9381 | 0.1902 | -0.9802 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9792 | -0.9699 | -0.5178 | -0.9228 | -0.3945 | -0.9507 | 0.8851 | -0.9770 | -0.0988 | 1.0000 | -0.8463 | 0.9819 | 0.9974 | -0.9712 | -0.5478 | -0.1503 | 0.8756 | 0.9754 | -0.9767 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.8650 | -0.9205 | -0.5970 | -0.9380 | -0.5781 | -0.9611 | -0.4113 | -0.9625 | -0.9955 | -0.9657 | -0.8465 | 0.9813 | 0.9940 | -0.9342 | -0.5335 | -0.1503 | 0.8937 | 0.9314 | -0.9785 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.2192 | -0.9622 | 0.4041 | -0.3238 | -0.5534 | -0.8821 | -0.3972 | -0.9691 | -0.9832 | -0.9645 | -0.8794 | 0.9830 | 0.9953 | -0.9696 | -0.5478 | -0.4152 | 0.9518 | 0.9682 | -0.9687 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9055 | -0.9754 | -0.6805 | -0.8844 | -0.5312 | -0.9215 | -0.3818 | -0.9733 | -0.9700 | -0.9612 | -0.8374 | 0.9833 | 0.9959 | -0.9594 | -0.5410 | -0.1540 | 0.9529 | 0.9772 | -0.9792 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9367 | -0.9884 | -0.3302 | -0.8464 | -0.5777 | -0.7825 | -0.4167 | -0.9751 | -0.9924 | -0.9674 | -1.0000 | 0.9854 | 0.9978 | -0.9741 | -0.5478 | -0.1831 | 0.9482 | 0.9787 | -0.9779 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9204 | -0.9685 | -0.1379 | -0.9228 | -0.5995 | -0.9507 | -0.3944 | -0.9673 | -0.9985 | -0.9634 | -0.8504 | 0.9824 | 0.9954 | -0.9529 | -0.5478 | -1.0000 | 0.8756 | 0.9528 | -0.9793 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9475 | -0.9722 | -0.2420 | -0.6920 | -0.5580 | -0.9865 | -0.3338 | -0.9664 | -0.9863 | -0.9646 | -0.8374 | 0.9771 | 0.9921 | -0.9423 | -0.5470 | -0.2718 | 0.8937 | 0.9653 | -0.4868 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9165 | -0.9477 | -0.3710 | -0.5758 | -0.5442 | -0.9677 | -0.3266 | -0.9138 | -0.9861 | -0.9564 | -0.8490 | 0.9846 | 0.9982 | -0.9628 | -0.5461 | -0.1544 | 0.9277 | 0.9725 | -0.6566 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9460 | -0.9480 | -0.4349 | -0.7244 | -0.6015 | -0.9605 | -0.3475 | -0.6878 | -0.9892 | -0.9590 | -0.6954 | 0.9857 | 0.9982 | -0.9555 | -0.5453 | -0.1559 | 0.9431 | 0.9349 | -0.9503 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9710 | -0.9781 | -0.3237 | -0.6713 | -0.5947 | -0.7771 | -0.3274 | -0.9430 | -0.9816 | -0.9685 | -1.0000 | 0.9857 | 0.9982 | -0.9739 | -0.5478 | -0.1536 | 0.8937 | 0.9784 | -0.9798 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9297 | -0.9322 | -1.0000 | -0.8945 | -0.6907 | -0.9617 | -0.3988 | -0.9634 | -0.9969 | -0.9697 | -0.8519 | 0.9798 | 0.9965 | -0.9634 | -0.5377 | -0.1774 | 0.9277 | 0.9739 | -0.9781 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9799 | -0.9705 | -0.5787 | -0.8127 | -0.5291 | -0.8947 | -0.3224 | -0.9260 | -0.9856 | -0.9585 | -0.8389 | 0.9818 | 0.9965 | -0.9601 | -0.5389 | -0.1529 | 0.9508 | 0.9309 | -0.9790 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| 0.7082 | -0.9804 | -0.5533 | -0.9109 | -0.5870 | -0.8890 | -0.3944 | -0.9255 | -0.9945 | -0.9613 | -0.8448 | 0.9844 | 0.9963 | -0.9715 | -0.5473 | -0.1659 | 0.9080 | 0.9748 | -0.9795 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.5559 | -0.9758 | -0.6432 | -0.9464 | -0.5758 | -0.9975 | -0.4165 | -0.9719 | -0.9937 | -0.9645 | -0.8832 | 0.9842 | 0.9982 | -0.9738 | -0.5156 | -0.1986 | 0.7656 | 0.9782 | -0.9800 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9584 | -0.9789 | -0.6083 | -0.9059 | -0.5794 | -0.8124 | -0.3921 | -0.9702 | -0.9915 | -0.9418 | -0.8504 | 0.9718 | 0.9975 | -0.4248 | -0.4527 | -0.1584 | 0.9327 | 0.8710 | -0.9855 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9669 | -0.9687 | -0.4858 | -0.9418 | -0.5917 | -0.9689 | -0.4012 | -0.9673 | -0.9987 | -0.9679 | -0.8490 | 0.9864 | 0.9981 | -0.9699 | -0.5478 | -0.1505 | 0.9470 | 0.9760 | -0.9797 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9723 | -0.9715 | -0.6160 | -0.8205 | -0.5290 | -0.9390 | -0.3283 | -0.9530 | -0.9846 | -0.8680 | -0.8493 | 0.4596 | 0.5383 | -0.2204 | -0.5478 | -0.1681 | 0.9525 | 0.9250 | -0.9766 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9736 | -0.9450 | -0.6355 | -0.8772 | -0.5608 | -0.9420 | -0.3735 | -0.9759 | -0.9861 | 0.3268 | -0.6954 | 0.9844 | 0.9944 | -0.9716 | -0.5394 | -0.1682 | 0.9191 | 0.9707 | -0.9701 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9163 | -0.9240 | -0.6799 | -0.9591 | -0.5843 | -0.6358 | -0.4211 | -0.9679 | -0.9894 | -0.9456 | -0.8495 | 0.9834 | 0.9969 | -0.9686 | -0.5478 | -0.1503 | 0.8980 | 0.9783 | -0.9793 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9761 | -0.9571 | -0.6982 | -0.1530 | -0.0989 | -0.9823 | 0.0254 | -0.9760 | -0.4116 | -0.9368 | -0.6954 | 0.9750 | 0.9896 | -0.9439 | -0.5413 | -0.1528 | 0.7374 | 0.9608 | -0.9785 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
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| -0.9918 | -0.9730 | -0.4935 | -0.9303 | -0.4834 | -0.8797 | -0.3363 | -0.9777 | -0.9726 | -0.9847 | -0.8465 | 0.9852 | 0.9982 | -0.9735 | -0.5478 | -0.1589 | 0.9348 | 0.9770 | -0.9790 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.9740 | -0.9835 | -0.6089 | -0.3107 | -0.4925 | -0.9265 | -0.4269 | -0.9736 | -0.9911 | -0.9654 | -0.7030 | 0.9649 | 0.9772 | -0.9589 | -0.5478 | -0.1537 | 0.9399 | 0.7953 | -0.5289 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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| -0.9918 | -0.9801 | -0.5834 | -0.9555 | -0.5889 | -0.9531 | -0.4016 | -0.7764 | -0.9972 | -0.9592 | -0.8496 | 0.9859 | 0.9922 | -0.9623 | -0.5454 | -0.1722 | 0.9478 | 0.9749 | -0.9815 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
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| -0.8833 | -0.9670 | -0.2533 | -0.8845 | -0.5989 | -0.8309 | -0.4144 | -0.9747 | -0.9946 | -0.9671 | -0.8337 | 0.9817 | 0.9953 | -0.9728 | -0.5435 | -0.1526 | -1.0000 | 0.9656 | -0.9791 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9082 | -0.9665 | -0.5385 | -0.9251 | -0.5670 | -0.8384 | -0.4134 | -0.9740 | -0.9943 | -0.9676 | -0.8512 | 0.9857 | 0.9972 | -0.9708 | -0.5239 | -0.1586 | 0.8553 | 0.9767 | -0.9798 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9165 | -0.9759 | -0.6728 | -0.9873 | -0.8459 | 1.0000 | -0.4399 | 0.0065 | -0.9261 | -0.9559 | -0.8475 | 0.9637 | 0.9924 | -0.9740 | -0.5140 | -0.1530 | 0.9425 | 0.9457 | -0.9786 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9780 | -0.6960 | -0.2834 | -0.9116 | -0.5712 | -0.9471 | -0.4236 | -0.8020 | -0.9955 | -0.9655 | -0.8418 | 0.9841 | 0.9945 | -0.9520 | -0.5140 | -0.1644 | 0.8783 | 0.9679 | -0.9757 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9760 | -0.9693 | -0.7012 | -0.8413 | -0.5408 | -0.9199 | -0.4417 | -0.9747 | -0.8344 | -0.9404 | -0.8475 | 0.9758 | 0.9888 | -0.9664 | -0.5353 | -0.1569 | 0.9105 | 0.9502 | -0.8320 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.5765 | 1.0000 | -0.6633 | -0.6941 | -0.2236 | -0.9256 | -0.4547 | -0.9740 | -0.9466 | -0.9422 | -0.5882 | 0.9759 | 0.9851 | -0.9252 | -0.5107 | -0.1683 | 0.9503 | 0.8559 | -0.9783 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9469 | -0.9751 | -0.4260 | -0.7994 | -0.5634 | -0.8779 | -0.3591 | -0.9680 | -0.9878 | -0.9631 | -0.8354 | 0.9858 | 0.9981 | -0.9739 | -0.5478 | -0.1530 | 0.9437 | 0.9787 | -0.9788 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |
| -0.9918 | -0.9603 | -0.5905 | -0.7749 | -0.4220 | -0.9192 | -0.3998 | 1.0000 | -0.9812 | -0.9576 | -0.2309 | 0.9861 | 0.9928 | -0.9718 | -0.5435 | -0.1855 | 0.9503 | 0.9688 | -0.9771 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 0.0000 |
| -0.9716 | -0.9766 | -0.6095 | -0.9062 | -0.5756 | -0.8882 | -0.3746 | -0.9691 | -0.9908 | -0.9276 | -0.4843 | 0.9856 | 0.9783 | -0.9727 | -0.5475 | -0.1530 | 0.9234 | 0.9770 | -0.9791 | -0.9752 | -1.0000 | -1.0000 | 1.0000 | -1.0000 | -0.9978 | 1.0000 |

| I&Tm | Pbt | Dvd | Shf | Prt | Rce | Tm | Csa | Grp | Dpn | Oxp | Opl | Ocm | Rsv | Cap | Deb | Wcp | Nte | Ctx | Ovd | Dts | Cts | Toe | Cnr | Lqr | Sal | Asc | Gm | Prm | Rsh | Rce | Rtn | Icv |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -0.9849 | -0.9813 | 0.9440 | -0.9589 | -0.5691 | -0.3179 | -0.9793 | 0.9112 | -0.9705 | -0.9766 | 0.9725 | -0.7476 | -0.9769 | -0.9450 | -0.9901 | 0.9870 | -0.9728 | -0.9437 | 0.9718 | 0.9516 | -0.7078 | 0.7985 | -0.9807 | -0.9341 | -0.9888 | 0.8306 | -0.9812 | -0.7333 | 0.3619 | -0.2304 | -0.0811 | 0.4024 | -0.7407 |
| -0.9165 | -0.9685 | 0.9418 | -0.9478 | -0.7349 | -0.3595 | -0.9507 | 0.9084 | -0.9385 | -0.9721 | 0.9511 | -0.7481 | -0.9782 | -0.9361 | -0.9631 | 0.9792 | -0.9631 | -0.9164 | 0.9788 | 0.9567 | -0.6181 | 0.7488 | -0.9725 | -0.9886 | -0.9495 | 0.5184 | -0.9833 | -0.7275 | 0.3146 | -0.2871 | -0.1456 | 0.2547 | -0.7612 |
| -0.9807 | -0.9742 | 0.9484 | -0.9680 | -0.6319 | -0.3572 | -0.9886 | 0.9360 | -0.9861 | -0.9990 | 0.9772 | -0.7747 | -0.9886 | -0.9551 | -0.9759 | 0.9932 | -0.9749 | -0.9219 | 0.9755 | 0.9545 | -0.7142 | 0.8012 | -0.9837 | -0.8079 | -0.9863 | 0.4380 | -0.9833 | -0.6883 | 0.3212 | -0.2831 | -0.1425 | 0.2561 | -0.7619 |
| -0.7183 | -0.0592 | -1.0000 | -0.5273 | 1.0000 | -0.3298 | -0.5949 | 0.9369 | -0.9852 | 1.0000 | 0.5191 | -0.7691 | 0.3119 | 1.0000 | 1.0000 | -1.0000 | 1.0000 | 1.0000 | -0.9285 | -1.0000 | -0.7135 | 0.7852 | 1.0000 | -0.9132 | -0.8577 | 0.0804 | -0.9786 | -0.4916 | 0.3244 | -0.1984 | -0.1067 | 0.2277 | -0.7625 |
| -0.9833 | -0.9746 | 0.9504 | -0.9845 | -0.6049 | -0.3833 | -0.9902 | 0.9552 | -0.9802 | -0.9743 | 0.9779 | -0.7604 | -0.9782 | -0.9528 | -0.9806 | 0.9903 | -0.9691 | -0.9386 | 0.9725 | 0.9601 | -0.6853 | 0.7852 | -0.9821 | -0.9477 | -0.9234 | 0.2850 | -0.9809 | -0.6850 | 0.3213 | -0.2889 | -0.1505 | 0.2279 | -0.7623 |
| -0.9980 | -0.8741 | 0.9471 | -0.9615 | -0.6421 | -0.3670 | -0.9988 | 0.9369 | -0.9852 | -0.9998 | 0.9784 | -0.7691 | -0.9779 | -0.9485 | -0.9864 | 0.9707 | -0.9718 | -0.9443 | 0.9188 | 0.9554 | -0.7106 | 0.7988 | -0.9773 | -0.8971 | -0.8805 | 0.4718 | -0.9888 | -0.6883 | 0.5062 | -0.2708 | -0.1553 | 0.2401 | -0.7622 |
| -0.6006 | -0.6926 | 0.8286 | -0.8320 | 0.1155 | -0.3236 | -0.7640 | -0.1620 | -0.8949 | -0.9976 | 0.9625 | -0.3759 | -0.9782 | -0.8116 | -0.9065 | 0.9550 | -0.9687 | -0.6291 | 0.9211 | 0.8842 | -0.6832 | 0.3462 | -0.9809 | -0.7822 | -0.9357 | 0.4588 | -0.9818 | -0.7215 | 0.3633 | -0.2226 | -0.0887 | 0.3640 | -0.7546 |
| -0.9753 | -0.9659 | 0.9465 | -0.9688 | -0.6323 | -0.2769 | -0.9854 | 0.9456 | -0.9707 | -0.9926 | 0.9704 | -0.7507 | -0.9783 | -0.9599 | -0.9652 | 0.9944 | -0.9761 | -0.9391 | 0.9168 | 0.9588 | -0.6894 | 0.7901 | -0.9852 | -0.9164 | -0.8892 | 0.3307 | -0.9834 | -0.7066 | 0.3625 | -0.1498 | -0.0376 | 0.4452 | -0.7583 |
| -0.6387 | 0.0591 | -1.0000 | -0.6222 | 1.0000 | -0.3095 | -0.9047 | 0.4900 | -0.8167 | 0.6190 | 1.0000 | 0.1659 | 0.0030 | 1.0000 | 1.0000 | -1.0000 | 1.0000 | 1.0000 | -1.0000 | -1.0000 | 1.0000 | 0.8064 | 1.0000 | -0.8923 | -0.8263 | 0.1670 | -0.9861 | -0.6784 | 0.3795 | -0.1587 | -0.0803 | 0.2980 | -0.7536 |
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| -0.8158 | -0.7437 | 0.8725 | -0.8700 | -0.2291 | -0.3154 | -0.9787 | 0.8906 | -0.9802 | -0.9900 | 0.9768 | -0.7544 | -0.9686 | -0.9533 | -0.9889 | 0.9903 | -0.9747 | -0.9346 | 0.9687 | 0.9500 | -0.6793 | 0.7798 | -0.9850 | -0.9051 | -0.8947 | 0.4234 | 1.0000 | -0.7228 | 0.2862 | -0.3088 | -0.2036 | 0.1454 | -0.7680 |
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| -0.9716 | -0.9693 | 0.9484 | -0.9663 | -0.6524 | -0.3153 | -0.8317 | 0.2158 | -0.8949 | -0.9853 | 0.9625 | -0.3904 | -0.9578 | -0.8334 | -0.8362 | 0.9903 | -0.8913 | -0.7092 | 0.9319 | 0.7218 | -0.6797 | 0.4866 | -0.9158 | -0.8103 | -0.9412 | 0.8198 | -0.9938 | -0.7428 | 0.4056 | -0.2175 | -0.0587 | 0.4457 | -0.7541 |
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| -0.9805 | -0.8749 | 0.9509 | -0.9653 | -0.6444 | -0.3567 | -0.9959 | 0.9719 | -0.9889 | -1.0000 | 0.9790 | -0.7749 | -0.9782 | -0.9633 | -0.9582 | 0.9918 | -0.9780 | -0.9448 | 0.9728 | 0.9634 | -0.7135 | 0.7852 | -0.9858 | -0.9510 | -0.9166 | 0.2676 | -0.9888 | -0.6065 | 0.2829 | -0.3070 | -0.1776 | 0.1736 | -0.7633 |
| -0.9931 | -0.8781 | 0.9527 | -0.9710 | -0.7134 | -0.3840 | -0.9843 | 0.9251 | -0.9786 | -0.9914 | 0.9730 | -0.7746 | -0.9783 | -0.9570 | -0.9814 | 0.9993 | -0.9749 | -0.9400 | 0.9738 | 0.9539 | -0.6873 | 0.7674 | -0.9862 | -0.9317 | -0.9275 | 0.3017 | -0.9392 | -0.7110 | 0.2925 | -0.2994 | -0.1896 | 0.1806 | -0.7635 |
| -0.9734 | -0.8787 | 0.9502 | -0.9683 | -0.6246 | -0.3933 | -0.9873 | 0.9719 | -0.9852 | -0.9806 | 0.9529 | -0.7601 | -0.9773 | -0.9577 | -0.9735 | 0.9936 | -0.9759 | -0.9424 | 0.9727 | 0.9574 | -0.6954 | 0.7867 | -0.9848 | -0.9172 | -0.8782 | 0.3783 | -0.9839 | -0.7034 | 0.2817 | -0.3119 | -0.1946 | 0.1487 | -0.7639 |
| -0.9785 | -0.8801 | 0.9530 | -0.9680 | -0.6697 | -0.3971 | -0.9650 | 0.9646 | -0.9518 | -0.9860 | 0.9559 | -0.7705 | -0.9643 | -0.9145 | -0.9776 | 0.9700 | -0.9572 | -0.9404 | 0.9703 | 0.9507 | -0.7101 | 0.7665 | -0.9610 | -0.8915 | -0.9330 | 0.6306 | -0.9837 | -0.7275 | 0.3112 | -0.2781 | -0.1580 | 0.2258 | -0.7620 |
| -0.9407 | -0.8725 | 0.9434 | -0.9307 | -0.5295 | -0.3698 | -0.9995 | 0.9930 | -0.9882 | -0.9999 | 0.9790 | -0.7717 | -0.9771 | -0.9555 | -0.9861 | 1.0000 | -0.9791 | -0.9448 | 0.9754 | 0.9543 | -0.7148 | 0.8062 | -0.9864 | -0.8778 | -0.7934 | 0.8884 | -0.9955 | -0.7273 | 0.8389 | -0.2401 | -0.0945 | 0.4379 | -0.7624 |
| -0.9991 | -0.8735 | 0.9481 | -0.9688 | -0.6301 | -0.3205 | -0.8358 | 0.9718 | -0.9891 | -0.8267 | 0.9722 | -0.7932 | -0.9230 | -1.0000 | -0.6051 | 0.9745 | -0.8904 | -0.8119 | 0.9687 | 0.9521 | -0.4888 | 0.6558 | -0.9130 | -0.8441 | -0.8290 | -0.2031 | -0.9751 | -0.8881 | 0.3523 | -0.3537 | -0.1160 | 0.3206 | -0.7605 |
| -0.7220 | -0.7711 | 0.9077 | -1.0000 | -0.5023 | -0.3367 | -0.9847 | 0.4860 | -0.9115 | -0.9853 | 0.9581 | -0.7749 | -0.9648 | -0.9116 | -0.9013 | 1.0000 | -0.9093 | -0.7405 | 0.9431 | 0.9208 | -0.3580 | 0.5139 | -0.9212 | -0.7613 | -0.8427 | 0.7050 | -0.9848 | -0.7430 | 0.4045 | -0.2347 | -0.0872 | 0.4097 | -0.7612 |
| -0.8048 | -0.7279 | 0.8989 | -0.8307 | -0.2421 | -0.3148 | -0.8769 | 0.9777 | -0.9816 | -0.9401 | 0.7292 | -0.7705 | -0.8720 | -0.9096 | -0.8390 | 0.9717 | -0.9407 | -0.8960 | 0.9528 | 0.9308 | -0.6058 | 0.6735 | -0.9533 | -0.8794 | -0.9042 | 0.5716 | -0.9884 | -0.7303 | 0.3484 | -0.2295 | -0.0815 | 0.3855 | -0.7562 |
| -0.7916 | -0.8036 | 0.9147 | -0.9095 | -0.3044 | -0.3161 | -0.9988 | 0.9888 | -0.9885 | -0.9985 | 0.9789 | -0.7748 | -0.9644 | -0.9384 | -0.9891 | 1.0000 | -0.9734 | -0.9442 | 0.9728 | 0.9498 | -0.7140 | 0.8056 | -0.9790 | -0.8600 | -0.4569 | 0.9428 | -0.9839 | -0.7442 | 0.9095 | -0.2619 | -0.1304 | 0.3283 | -0.7596 |
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| -0.9539 | -0.9323 | 0.9290 | -0.9615 | -0.6419 | -0.4881 | -0.9934 | 0.9629 | -0.9859 | -0.9982 | 0.9771 | -0.7752 | -0.9773 | -0.9576 | -0.9854 | 1.0000 | -0.9782 | -0.9401 | 0.9561 | 0.9593 | -0.7081 | 0.8032 | -0.9855 | -0.5000 | -0.4446 | 0.8479 | -0.9959 | -0.7439 | 0.3209 | -0.2699 | -0.1434 | 0.2749 | -0.7610 |
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| 0.7613 | -0.3667 | 0.9535 | -0.7211 | 1.0000 | -0.3632 | -0.8566 | 0.3373 | -0.9065 | -0.8911 | 0.9587 | -0.5312 | -0.9795 | -0.9468 | -0.9387 | 0.9859 | -0.9675 | -0.9204 | 0.9701 | 0.9494 | -0.7214 | 0.7523 | -0.9786 | -0.8842 | -0.9029 | 0.5188 | -0.9773 | -0.7244 | 0.3312 | -0.2529 | -0.1208 | 0.2871 | -0.7598 |
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| | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
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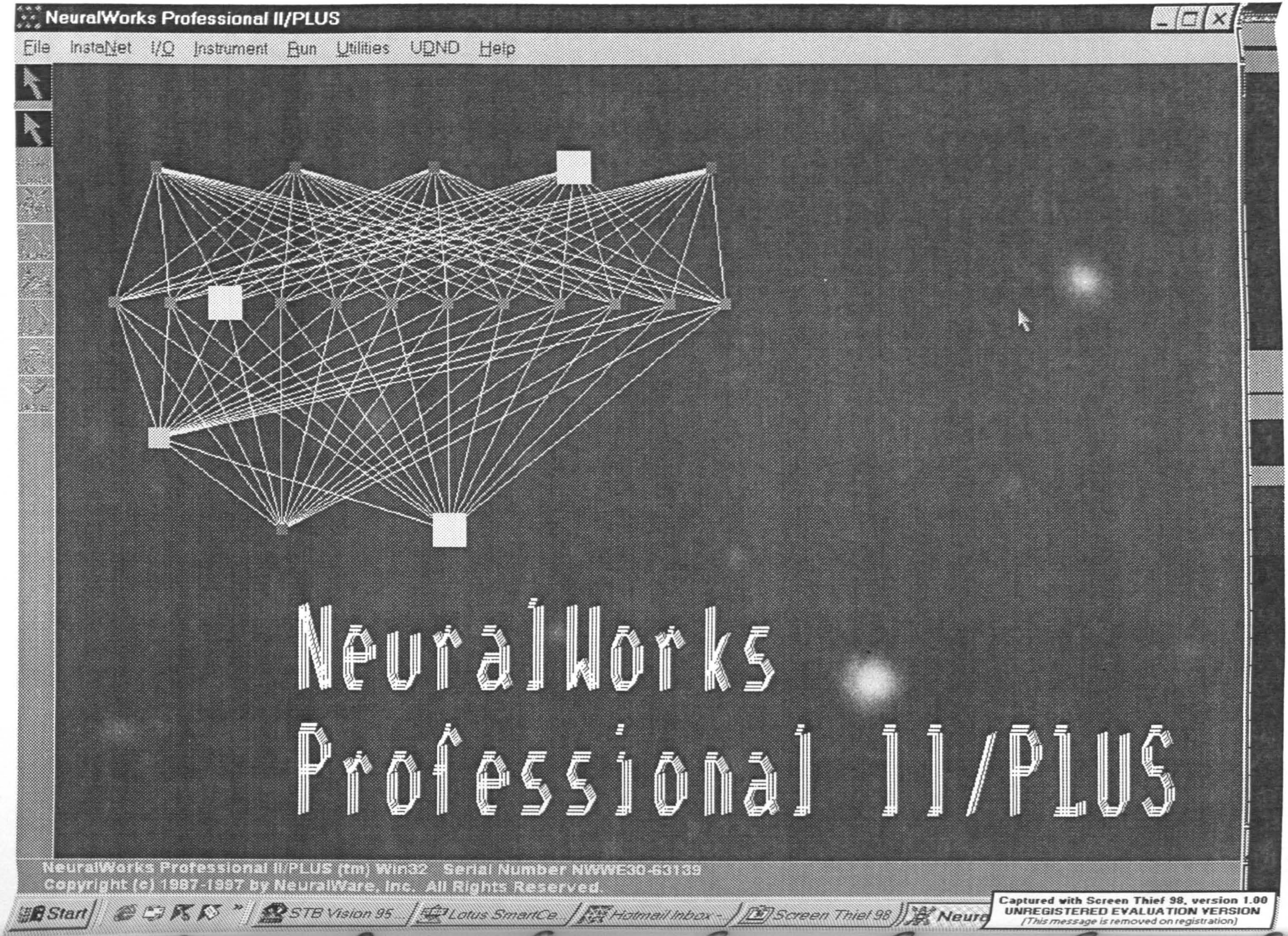
| -0.9867 | -0.8841 | 0.9261 | -0.9738 | -0.6191 | -0.5294 | -0.6839 | 0.8165 | -0.9556 | 0.4264 | 0.7269 | -0.7491 | -0.9230 | -0.9356 | -0.9545 | 0.9894 | -0.9605 | -0.9057 | 0.4545 | 0.4423 | -0.6760 | 0.7517 | -0.9739 | -0.9831 | -0.9713 | 0.7589 | -0.9844 | -0.7321 | 0.3293 | -0.2850 | -0.1672 | 0.1985 | -0.7706 |
| -0.9732 | -0.8669 | 0.9336 | -0.9727 | -0.2335 | -0.3603 | -0.9987 | 0.9859 | -0.9897 | -0.9702 | 0.9767 | -0.8287 | -0.9681 | -0.9589 | -0.9958 | 1.0000 | -0.9801 | -0.9442 | 0.9734 | 0.9515 | -0.7125 | 0.8057 | -0.9878 | -0.9252 | -0.8029 | 0.2839 | -0.1417 | -0.7338 | 0.3162 | -0.2154 | -0.0761 | 0.3074 | -0.6276 |
| -0.8541 | -0.8774 | 0.9521 | -0.9728 | -0.5911 | -0.3781 | -0.9997 | 0.9940 | -0.9894 | -0.9998 | 0.9783 | -0.7783 | -0.8787 | -0.9460 | -0.9903 | 0.9914 | -0.9683 | -0.9491 | 0.9707 | 0.9508 | -0.7101 | 0.7161 | -0.9805 | -0.9542 | -0.8288 | 0.5385 | -0.9858 | -0.7134 | 0.5380 | -0.2370 | -0.1209 | 0.3500 | -0.7582 |
| -0.8524 | -0.8600 | 0.8938 | -0.9751 | -0.5249 | -0.3063 | -0.9451 | 0.7429 | -0.9574 | -0.9788 | 0.9688 | -0.7011 | -0.9724 | -0.9521 | -0.9525 | 0.9885 | -0.9740 | -0.9442 | 0.9747 | 0.9531 | -0.7138 | 0.8045 | -0.9801 | -0.9421 | -0.9070 | 0.3131 | 0.0109 | -0.8584 | -1.0000 | -0.8858 | -0.5488 | -0.8203 | -0.7795 |

## Appendix H – Trained Neural Network Models A & B

The following pages contain some samples of fully trained neural networks used during the study. Some neural network architectures were tested during study to see if they can model the problem accurately. After many trials, it was decided to choose between a fully connected neural network and an inter-connected neural network. Recall that Model A is the fully connected network and Model B is the inter-connected neural network.


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
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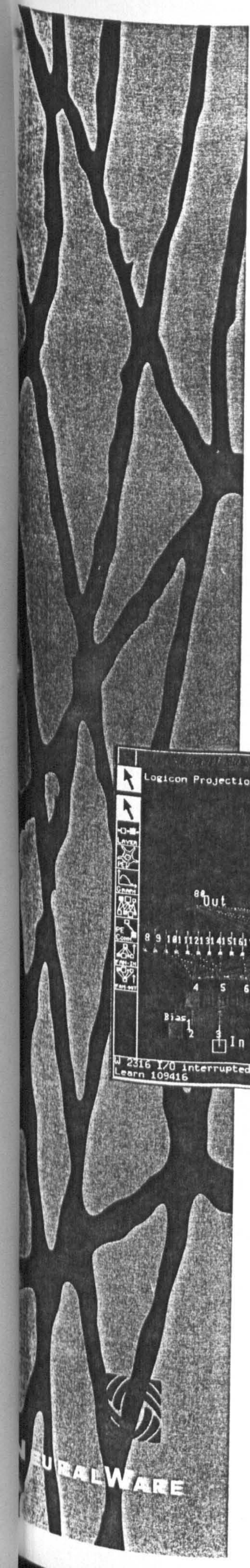
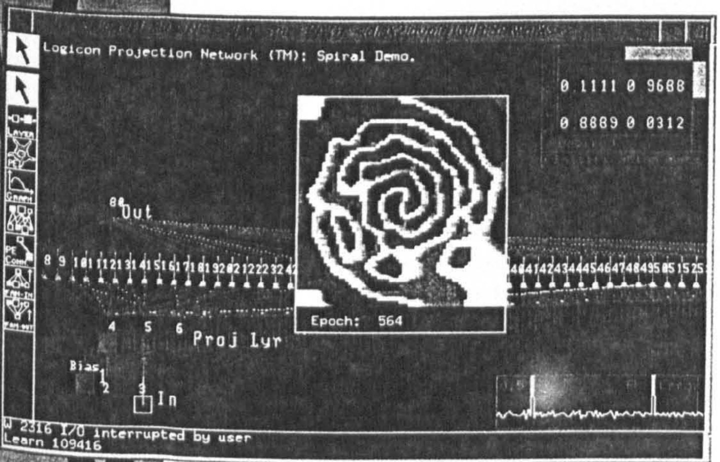


# NeuralWorks®
# Professional II/PLUS v5.2

## Your strategic competitive advantage

Whether you work in industry, finance, or defense, you know the necessity of maintaining a competitive edge. To keep that edge, many companies have turned to neural networks: powerful tools and techniques for signal processing, modeling, forecasting, and pattern recognition. Neural networks have easily replaced conventional systems using statistical methods, pattern recognition and classification, and linear and non-linear curve fitting. Neural networks provide an advantage through improved quality, productivity, and yield while reducing costs, down-time and scrap.

Neural network solutions are hard at work: **detecting fraud** in credit applications, insurance and warranty claims, and credit card fraud; **modeling and forecasting** in bankruptcy prediction, credit scoring, securities trading, portfolio evaluation, mail-list management, product marketing and targeted marketing; and in **process industries** for process modeling, process control, oil and gas exploration,




reservoir management, production line management, machine diagnostics, flaw detection, product development, and industrial inspection.

NeuralWare offers the highest quality development products. These products support the latest in application tested technology. They are available on a wide range of computing platforms. NeuralWare provides the training and support required to ensure that you succeed in the development and deployment of solutions which utilize neural network technology.

### Performance You Can Count On

*NeuralWorks Professional II / PLUS* is the world's standard in professional neural network development systems. *NeuralWorks* allows you to build, train, refine and deploy neural network solutions. For power, flexibility and support, nothing else even comes close. Consider these features:

***InstaNet:***™ This menu lets you select from any of the major network types to create any of the 28 major paradigms and dozens of variations supported by NeuralWare. Each major class of networks has its own custom menu with options and features specific to that class. For example, the Back-propagation Builder supports standard, cumulative, normalized-cumulative, Delta-Bar-Delta, Extended-Delta-Bar-Delta, Quickprop, and Maxprop learning rules, as well as Cascade architecture and the Logicon Projection Network™. Other major classes of networks include Learning Vector Quantization, Self-Organizing Map, General Regression Network, Genetic Reinforcement Learning, Probabilistic Neural Network, Radial Basis Function Networks, Counter Propagation, Modular Neural Network, Recurrent Networks, Reinforcement Learning, Fuzzy ARTMAP, and dialogs for special purpose networks or networks of historical significance (Adaline, Bi-directional Associative Memory, Brain-State-in-a-Box, Boltzman, Directed Random Search, Hamming, Hopfield, Madaline, Perceptron, Recirculation, and Spatio-Temporal Pattern Recognition).

***FlashCode:***™ Instantly create ANSI standard C code to deploy your fully trained network. FlashCode now supports all of the major network types. This does not require any additional hardware. You can use these routines to deploy your application, or combine networks together with other advanced technologies such as Expert Systems and Fuzzy Logic.

***SaveBest:***™ Prevent over-training with SaveBest. At user-specified intervals, the network is tested and the best-performing network is saved. Performance can be based on R-squared, RMS Error, Average Classification Rate or custom designed performance measure. This feature lets you train the network to the optimum degree based on the criteria which is right for your application.

***Optimize the Hidden Layer.*** An enhancement to SaveBest for non-linear feed-forward networks (Back-propagation) provides the capability of automatically optimizing the size of the hidden layer. Each hidden unit is ranked based on the degree to which it improves the objective function. Those units with a negative or minimal contribution are eliminated. This capability can be used in conjunction with the facility to periodically prune a network of small weights.

***ExplainNet:***™ This is a unique facility that tells you why a neural network made its decisions. It shows you which inputs to the model have the most impact on the network output. This is vital for applications like credit scoring. Together with utilities available from NeuralWare technical support, it can be used to do variable selection for building more robust models.

***Diagnostics.*** A wide variety of diagnostic tools to monitor network performance and diagnose problems are standard. Each of the major network types have specialized instruments which can be instantly created and used to observe specific activity. More general instruments can be created with NeuralProbe™. Custom instruments can be created using User IO extensions. All of the tools you need to build the best networks are at your fingertips.

***Graphical User Interface.*** No matter what platform you choose, you will find the same icon-based tool palettes and "mousable menus". Our interface is the same in every version of the product, making it easy to migrate to more powerful computing platforms.

***Batch Interface.*** User Control provides the capability for automating the neural network development process through a custom control interface with batch files. These control programs written in C can load, train, and test networks. You customize the operation of *Professional II / PLUS* to the rigorous demands of your production neural network development.

***Inter-platform compatibility.*** Not only does NeuralWare support a wide range of development environments, but data files and network files are fully interchangeable between them. This lets work groups in non-homogeneous computing environments transparently share data and network files.

***Flexible Architecture.*** You can customize the network architectures, develop training procedures, and substantially customize the operation of *NeuralWorks Professional II / PLUS* through the InstaNet IDL language. This is a built-in text-based scripting capability which can be used to architect a variety of neural network architectures and features.

## The NeuralWare Advantage

*NeuralWorks Professional II / PLUS* is the only neural network development tool backed with these advantages:

***Multi-platform support.*** *NeuralWorks Professional II / PLUS* currently runs on Sun workstations, INTEL 386-, 486- and Pentium-based personal computers, the Apple Macintosh, IBM RS/6000, NEC EWS-4800, HP 9000/700-800, and Silicon Graphics IRIS. NeuralWare provides transparent support for heterogeneous networks through ASCII network files. Kanji and Hangul are supported in certain countries. No matter what mix of hardware you have, or which platforms you pick in the future, *NeuralWorks Professional II / PLUS* is the obvious choice.

***Powerful options.*** *Designer Pack* allows you to go beyond the capabilities of FlashCode, by creating ANSI standard C code routines that incorporate all of the functionality of your networks, including the ability to learn. *User-Defined Neuro-Dynamics* allow you to modify the basic building blocks of a neural network so that you can modify existing architectures or create your own custom networks. (NOTE: These are available as separate products from NeuralWare.)

***Extensive training.*** When you buy *Professional II / PLUS*, you have the confidence of knowing that NeuralWare backs it up with training courses geared to your needs. Whether you are new to neural computing, looking for application specific insights, or advanced design, NeuralWare provides the training you need.

***Superior support.*** NeuralWare's support staff sets the standard for excellence in the field, and has consistently achieved the highest marks from customers.

***Award winning documentation.*** Over 1,000 pages of documentation address the whole range of needs. A tutorial helps you get started quickly. An in-depth reference book on neural computing is used as a text book in universities. A functionally organized user's guide provides in-depth technical information. Repeatedly, these documents have won awards for excellence from the Society for Technical Communication.

## Supported Platforms

***INTEL 386-, 486- and Pentium-based Personal Computers***
Processor: 80386, 80486.
Memory: 640K base with 2 MB extended memory. Math Co-processor: 486DX or INTEL 80387 required for 386/486-native mode operation. May not be compatible with non-INTEL math co-processors.
Disk Space: 6.0 MB. Operating System: DOS 5.0 or later with EMM-DPMI support.
Mouse: optional 2- or 3-button mouse with Microsoft-compatible version 7.03 or later driver. Graphics: Monochrome or color, EGA, VGA, SVGA, NEC 9801.
Media: 3.5" 1.44 MB or 5.25" 1.2 MB diskettes.

***Apple Macintosh***
Model: Any 68000 family Macintosh which supports System 6.0.5 or later.
Memory: 4.0 MB of application memory.
Math Co-processor: Strongly recommended, though not required. Disk Space: 5.0 MB.
Operating System: System 6.0.5 or later.
Mouse: 1-button mouse required.
Graphics: Monochrome or color.
Media: 800 KB 3.5" diskettes.

***Sun Sparc, Sun 4, compatibles***
Memory: 16 MB (24 MB recommended).
Disk Space: 11 MB. Operating System: SunOS 4.1.3 or above, Solaris 1.x, 2.x.
Mouse: 2- or 3-button mouse required.
Graphics: X11R4 or above, including OpenWindows 2.0
Media: 3.5" 1.44 MB diskettes or QIC Tape.

***IBM RS/6000***
Memory: 16MB (24 MB recommended).
Disk Space: 11 MB.
Operating System: AIX 3.2.
Mouse: 2- or 3-button mouse required.
Graphics X11R4 or above, including AIX Windows. Media: 3.5" 1.44 MB diskettes.

***NEC EWS-4800/22, EWS-4800/260***
Memory: 16MB (24 MB recommended).
Disk Space: 11 MB. Operating System: EWS-UX release 9.1 or above.
Mouse: 2- or 3-button mouse required.
Graphics: any X11R4 or above.
Media: .25" Cartridge Magnetic Tape (CMT).

***Silicon Graphics IRIS***
Memory: 16 MB (24 MB recommended).
Disk Space: 11 MB. Operating System: IRIX 4.0.5 and above. Mouse: 2- or 3-button mouse required. Graphics: Any X11R4 or above. Media: Medium density DAT tape.

***HP 9000/700, 800 series***
Memory: 16 MB (24 MB recommended).
Disk Space: 11 MB. Operating System: HPUX 8.07 or above. Mouse: 2- or 3-button mouse required. Graphics: Any X11R4 or above. Media: Medium density DAT tape.

## Order Today

Get the *NeuralWorks Professional* Advantage. Call NeuralWare today at (412) 787-8222 or by FAX at (412) 787-8220 to order your copy of *NeuralWorks Professional II / PLUS.*

# NeuralV
# DataScul

## The Power to Solve Data Analysis and Transformation Problems

### Attacking the Real Problem

It's a fact: when developing a neural network solution you'll spend over 80 percent of your time just sifting through and massaging data. First you must extract the data from your data base and convert it to a format that a neural network can use. The data may reside in a relational data base manager, a spreadsheet or a mainframe data base. Or worse, it may come from a variety of sources.

Once you have the data, you must arrange it, transform it, and then create training and test sets. Usually this requires a battery of tools, including spreadsheets, statistical packages, graphing packages, data base management systems, and text editors. If you're a programmer, you might write custom code to preprocess the data. And of course, you'll need to process the network output into something that your target system can use.

Wouldn't it be great if you had a single software solution that could do all of the things performed by an array of data manipulation tools? V it be even better if the tool was easy-to-u as fast and efficient?

### Introducing DataSculptor

*DataSculptor* is the world's first graphical analysis and transformation system for A cations. Using an intuitive interface, *Data* allows you to retrieve data from a variety sources, including NeuralWare data files, DBase II, III, and IV; Excel; Paradox; free and delimited ASCII files or binary files. I can be merged, sieved, sorted, viewed, tran formed, graphed, and written into network ready files. You can also use *DataSculptor* transform network output into a form your application can use. And it does it all from Microsoft Windows.

In short, *DataSculptor* is your solution for and easy data retrieval and transformatio yet, it will drastically reduce the time you working with your data.

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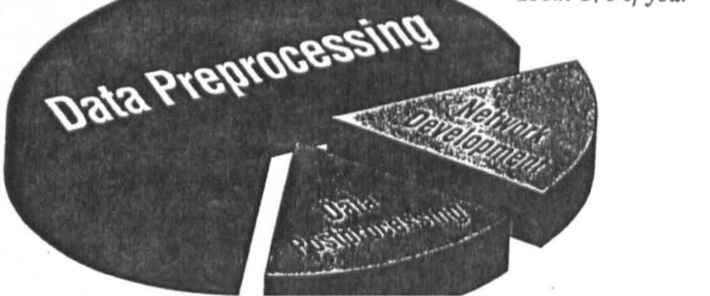
### The Typical Neural Network Development Process

*Step 1. You'll spend about 2/3 of your time just getting the data ready for your neural network.*

*Step 2. Actual network dev ment and testing only about 1/6 of your*



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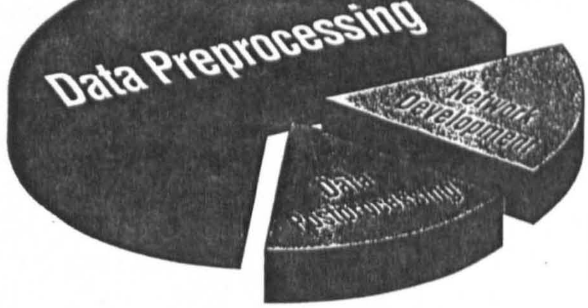


*Step 3. After the network is done, you'll spend another 1/6 of the project in processing the network output into a form that your applications can use.*

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# NeuralWare® DataSculptor™

## Version 1.51 Update

## Automatic Data Preprocessing

It is a well documented fact that preparing data for a neural network is one of the most difficult and time consuming aspects of creating neural network applications. With the new Automatic Data Preprocessor, DataSculptor gives the neural network novice the ability to create expert-class solutions to your data preprocessing problems.

For experienced data preprocessors, this feature offers you a way to verify your transformations or get expert suggestions for alternate transformation methods.

The expertise of years of work building neural network solutions to database problems has been distilled into this feature.

## Importing FlashCode to Embed Neural Networks

This new feature allows you to import your trained neural network into a DataSculptor project. You can also apply this to neural network deployment needs.

Embedding neural networks allows you to use one neural network to estimate missing data for input to another neural network for stock picking, insurance underwriting, target marketing, and other applications. It also lets you reverse data transformations that you made using DataSculptor to prepare the original data for the neural network.

## Improved Merge Object

The Merge object has been enhanced to provide several merge type options. You can now specify how two data sets are merged together.

### Relational Merge

If you are working with multiple data sets that contain related data with some common information (time or date for instance) you might need to combine all those separate files into one comprehensive file. This is often necessary for correlation, predictive, or other analytical studies. The Relational merge matches records from each data set according to a selected criterion – for example, time and date stamps, product, vendor, or customer information.

For process control engineers, data is often gathered from dozens of different instruments, each using different time intervals. Using DataSculptor's relational merge, a single file can be created that contains a complete set of data. This data set can then be used to perform model predictive control analyses, regression analyses, or causality and correlation studies, among other things.

Process control engineers, manufacturing specialists, and others will find this a great enhancement to DataSculptor's preprocessing power.

### The Other Merges

DataSculptor's original merge function merges two data sets record to record. We call this the Zipper merge.

The third merge combines two data sets (containing the same fields) end to end, and is called a Splice merge.

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*202 Park West Drive*

*Pittsburgh, PA 15275*

Phone: 412.787.8222
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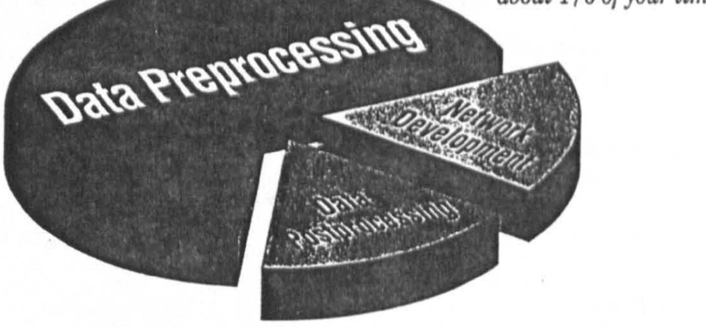


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*202 Park West Drive*

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Phone: 412.787.8222
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# NeuralWorks Professional II/PLUS Release 5.3

* FlashCode support for integrating with C++

* FlashCode to support static arrays
  Benefit: Better support for compiling FlashCode
  Better support for integration of FC with C++

* New instrument for SOM weights
  Benefit: Easier to visualize SOM internal configuration

* Contribution instrument for PEs
  Benefit: Additional method identifying importance of inputs and PEs for variable selection and pruning

* Linear Correlation Strip Chart instrument
  Benefit: Additional information when training networks for prediction

* Autodetect logical variables in min/max table & scale accordingly
  Benefit: Better network performance when many variables are used

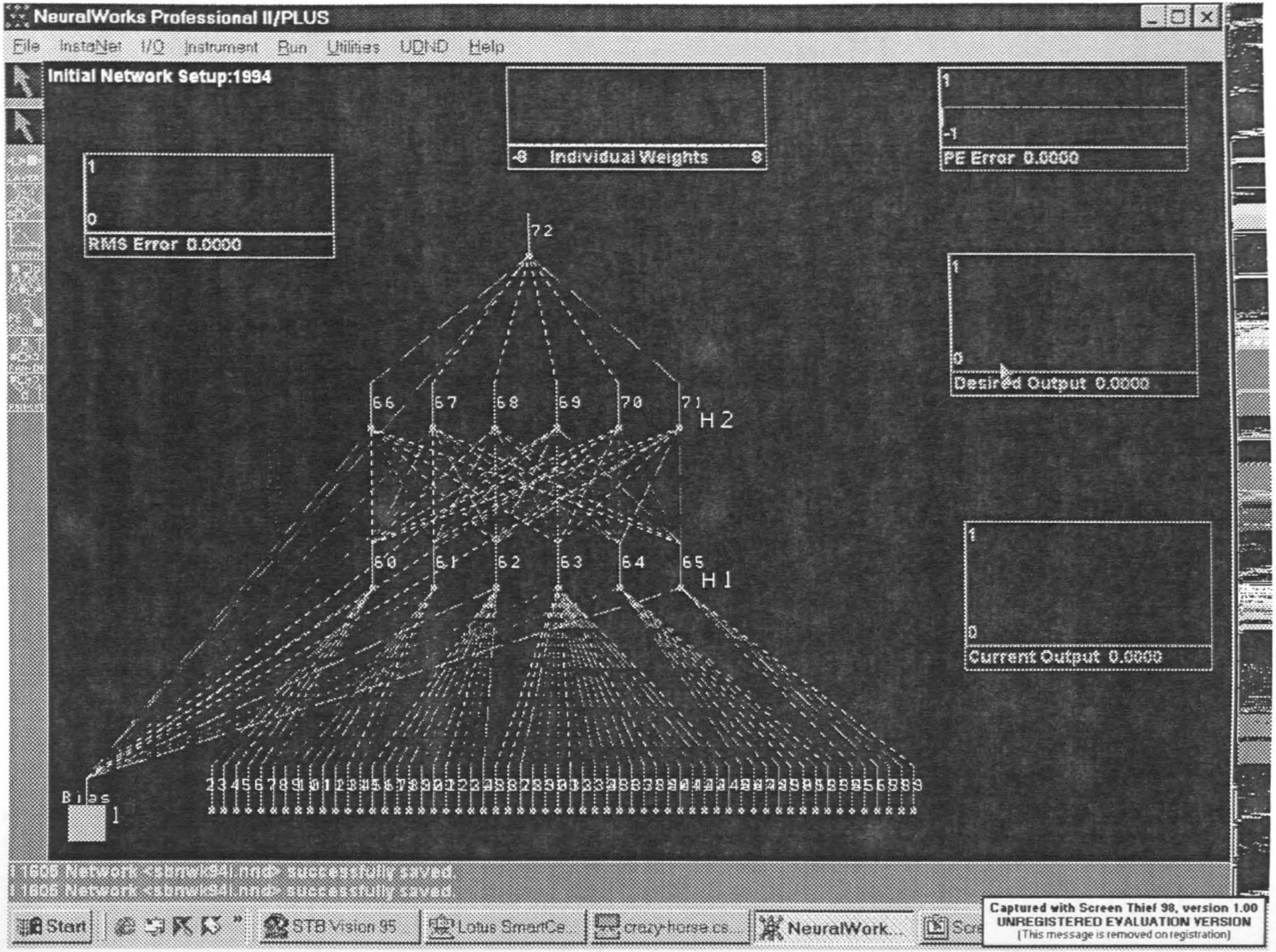
* Function key to disable & set PE output to zero / re-enable
  Benefit: Easier to examine the impact of a missing input

* Read PE names from file header
  Benefit: Networks are easier to understand

* Read comma separated files
  Benefit: Better support for data input

* Use average value of PE for pruning (vs. min/max)
  Benefit: Better pruning algorithm yielding smaller networks

* Bugs
  Make point-to-point connections default in connect PE
  Other miscellaneous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PE Error 0.0000
Desired Output 0.0000
Current Output 0.0000
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H1
Bias
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1606 Network <sbnwk94l.nnd> successfully saved.
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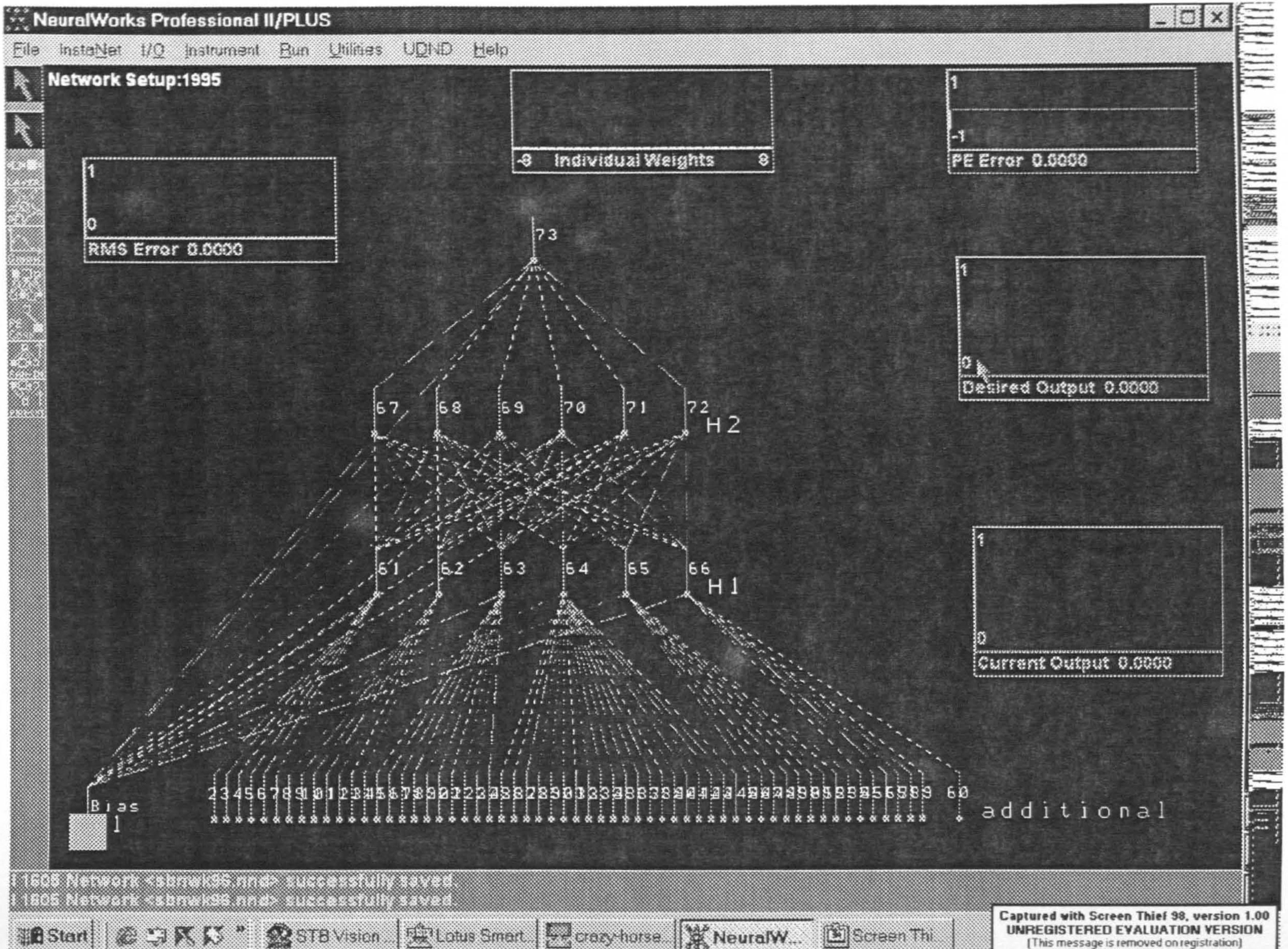
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H2
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Bias
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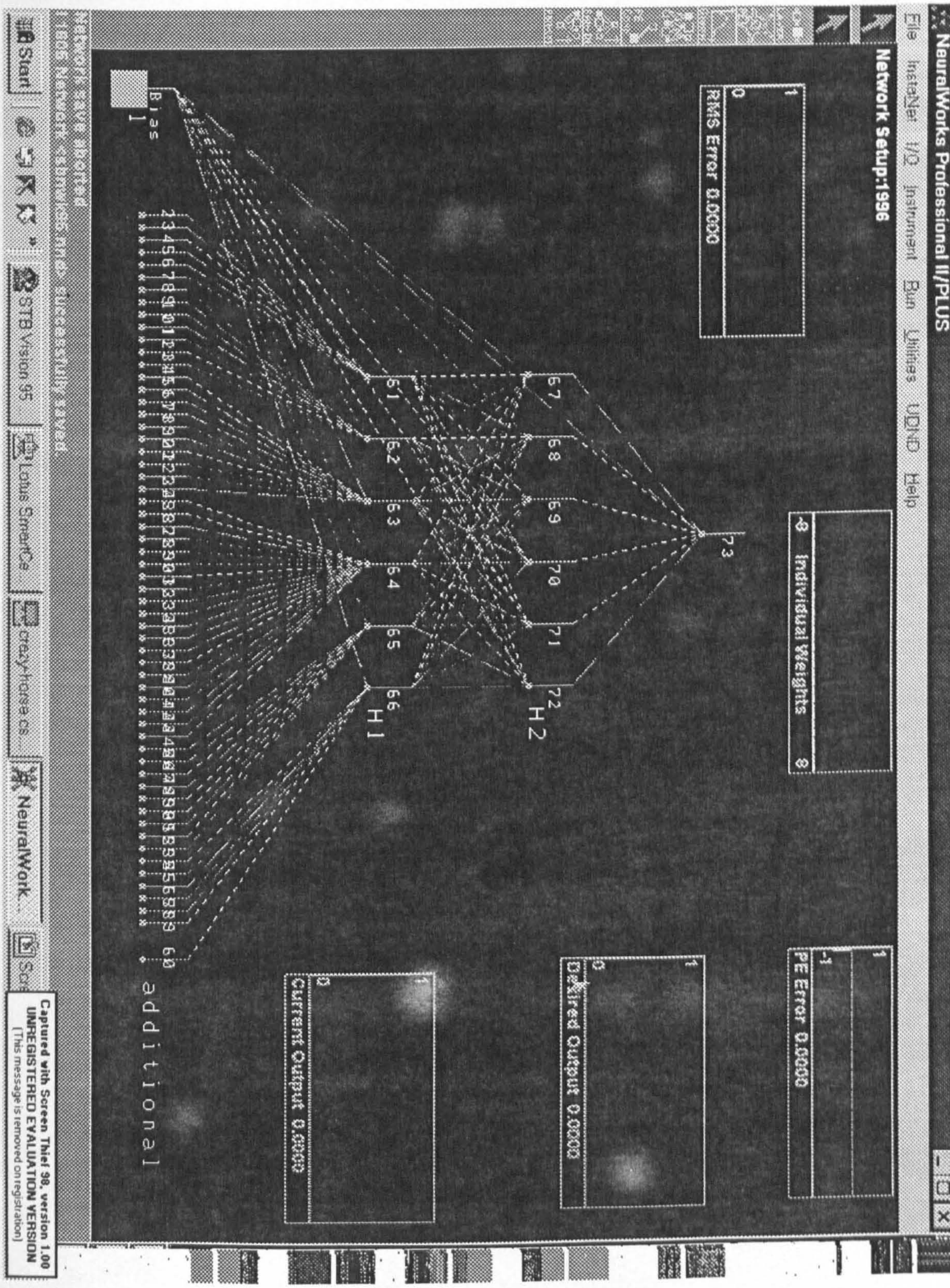
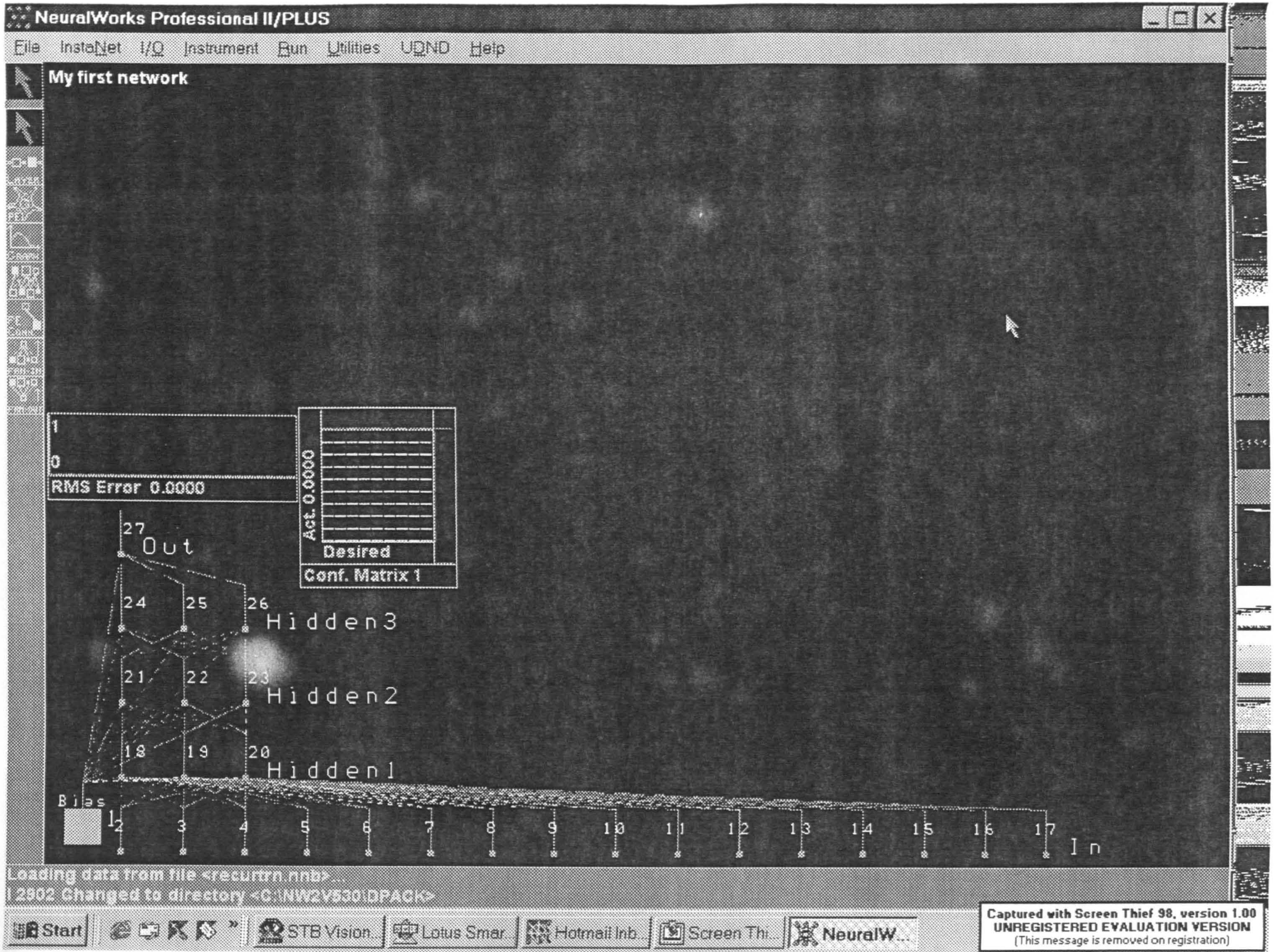
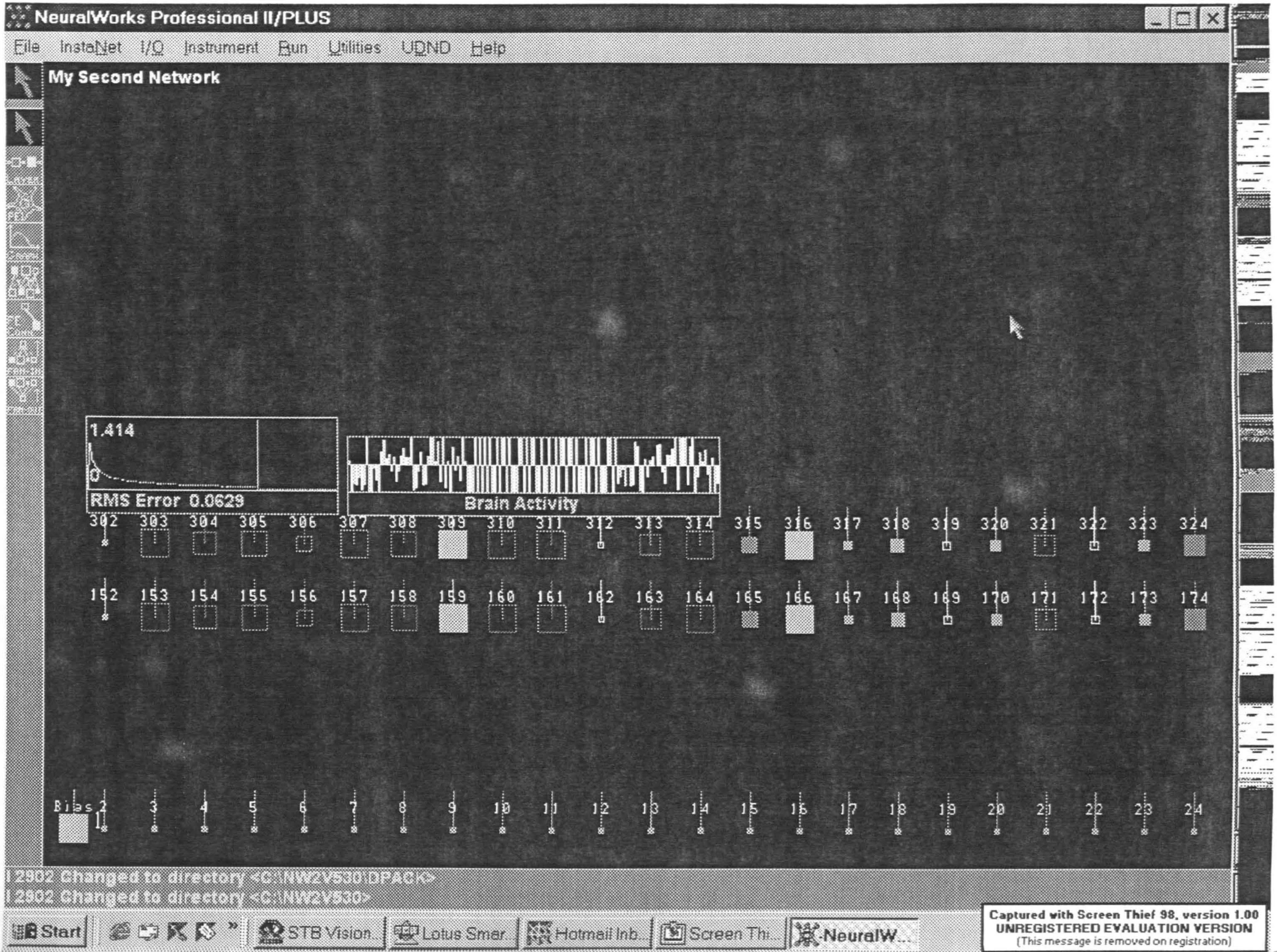
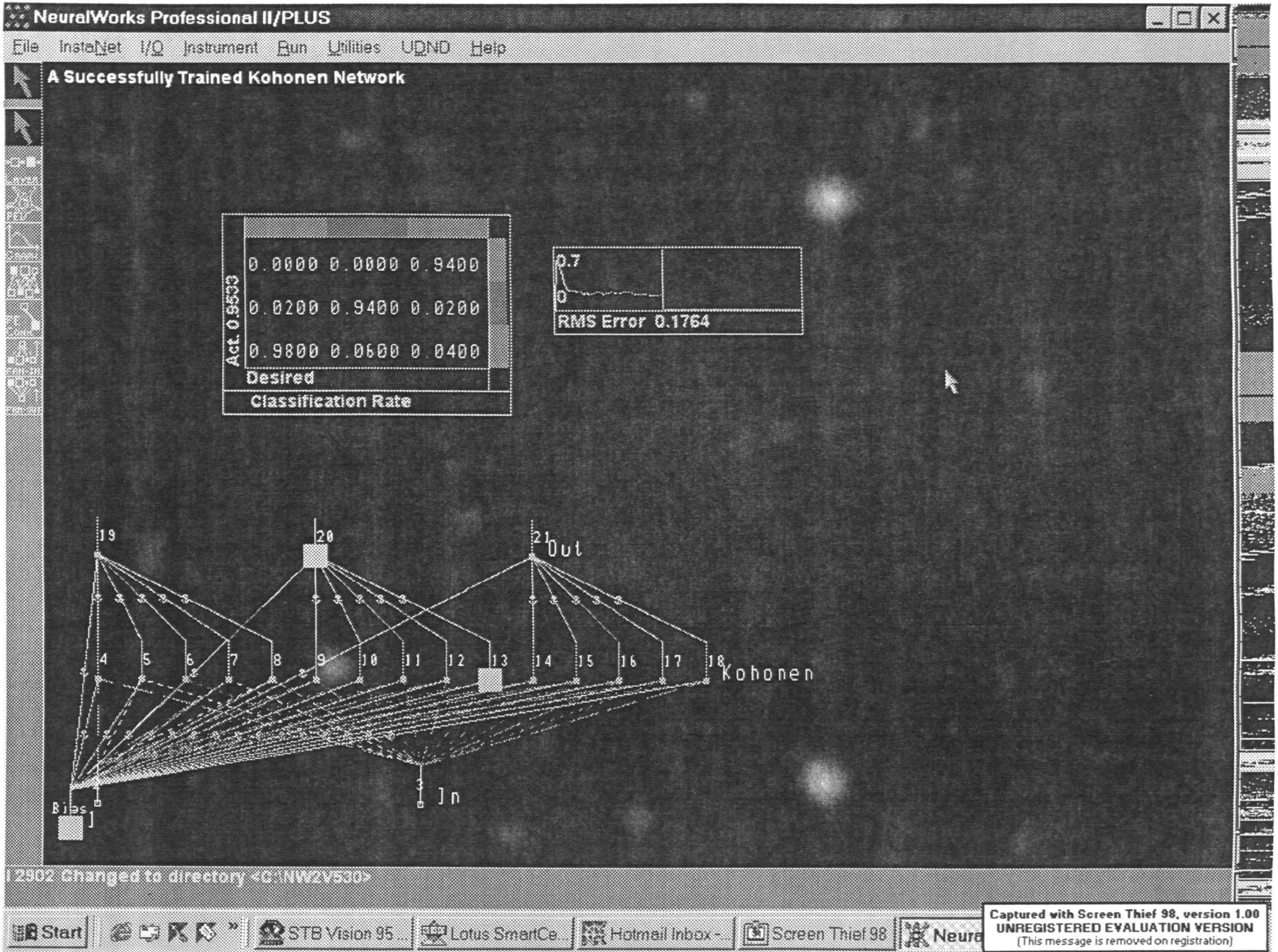
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
[This message is removed on registration]

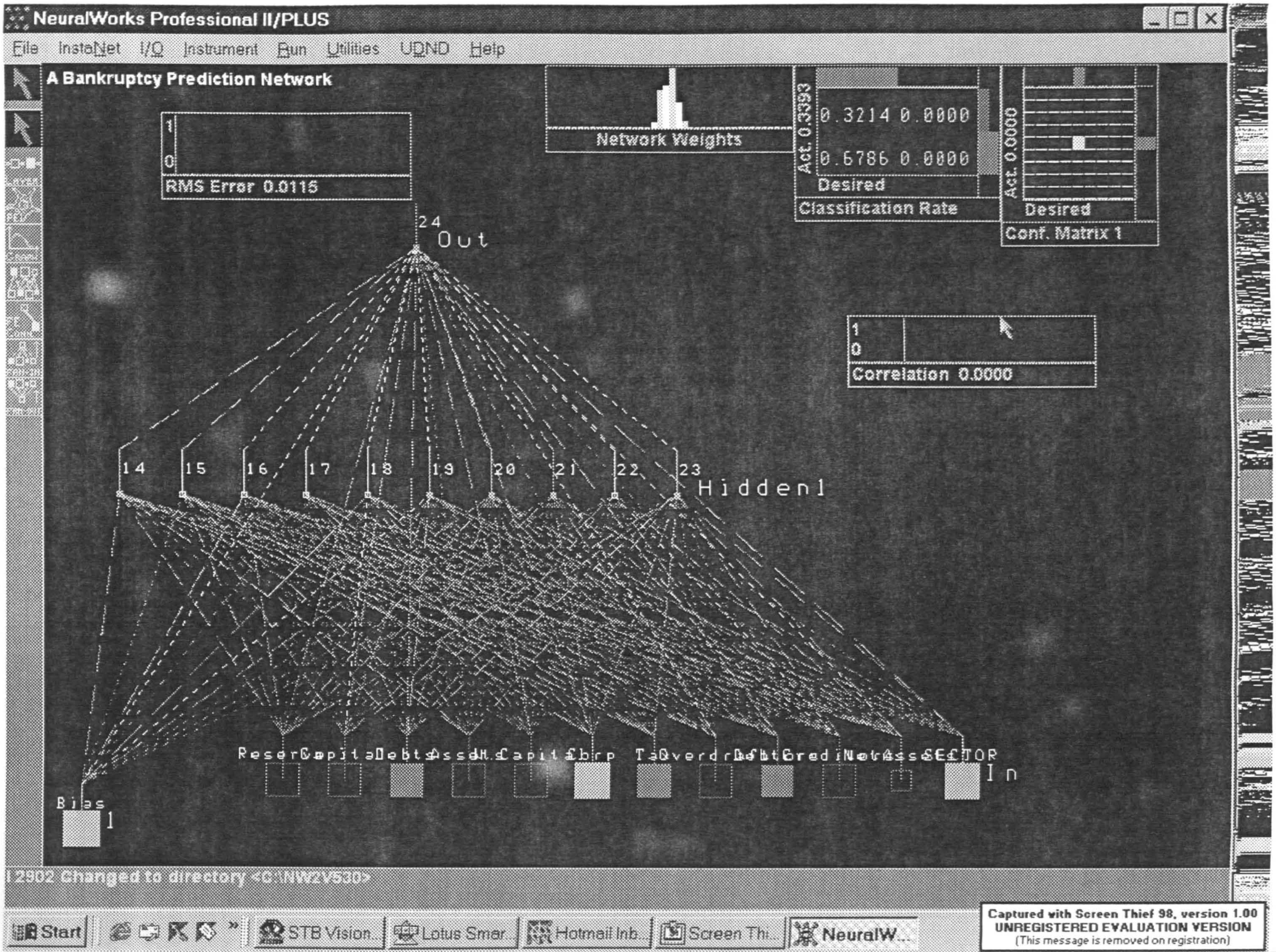

NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
Network Setup:1996
RMS Error 0.0000
Individual Weights
PE Error 0.0000
Desired Output 0.0000
Current Output 0.0000
Bias
H1
H2
additional
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
[This message is removed on registration]

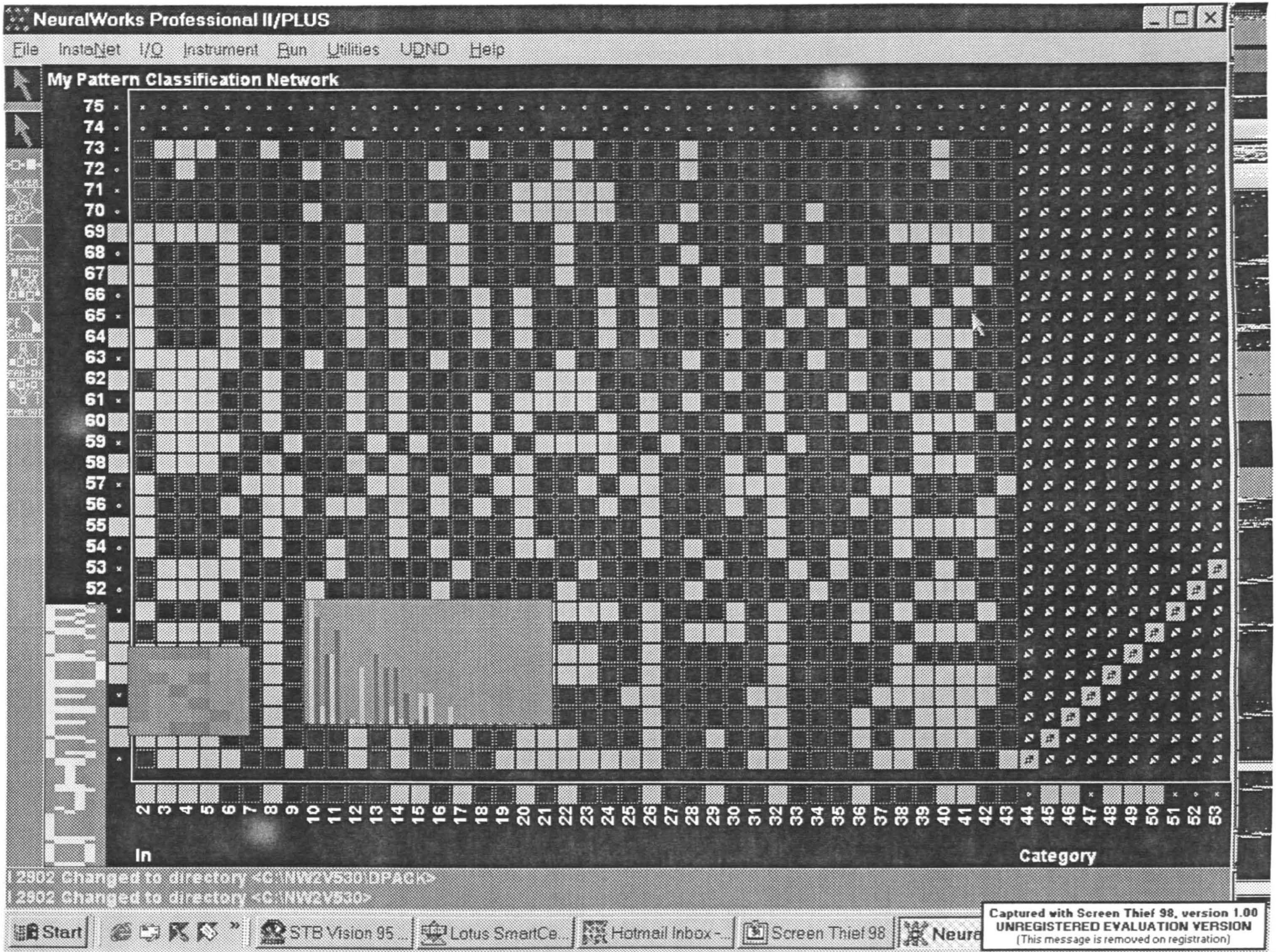

NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
My first network
1
0
RMS Error 0.0000
Act. 0.0000
Desired
Conf. Matrix 1
27 Out
24 25 26 Hidden3
21 22 23 Hidden2
18 19 20 Hidden1
Bias
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 In
Loading data from file <recurrn.nnb>...
I 2902 Changed to directory <C:\NW2V530\DPACK>
Start
STB Vision...
Lotus Smar...
Hotmail Inb...
Screen Thi...
NeuralW...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
My Second Network
1.414
0
RMS Error 0.0629
Brain Activity
302 303 304 305 306 307 308 309 310 311 312 313 314 315 316 317 318 319 320 321 322 323 324
152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174
Bias 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24
I 2902 Changed to directory <C:\NW2V530\DPACK>
I 2902 Changed to directory <C:\NW2V530>
Start STB Vision Lotus Smar Hotmail Inb Screen Th NeuralW...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)

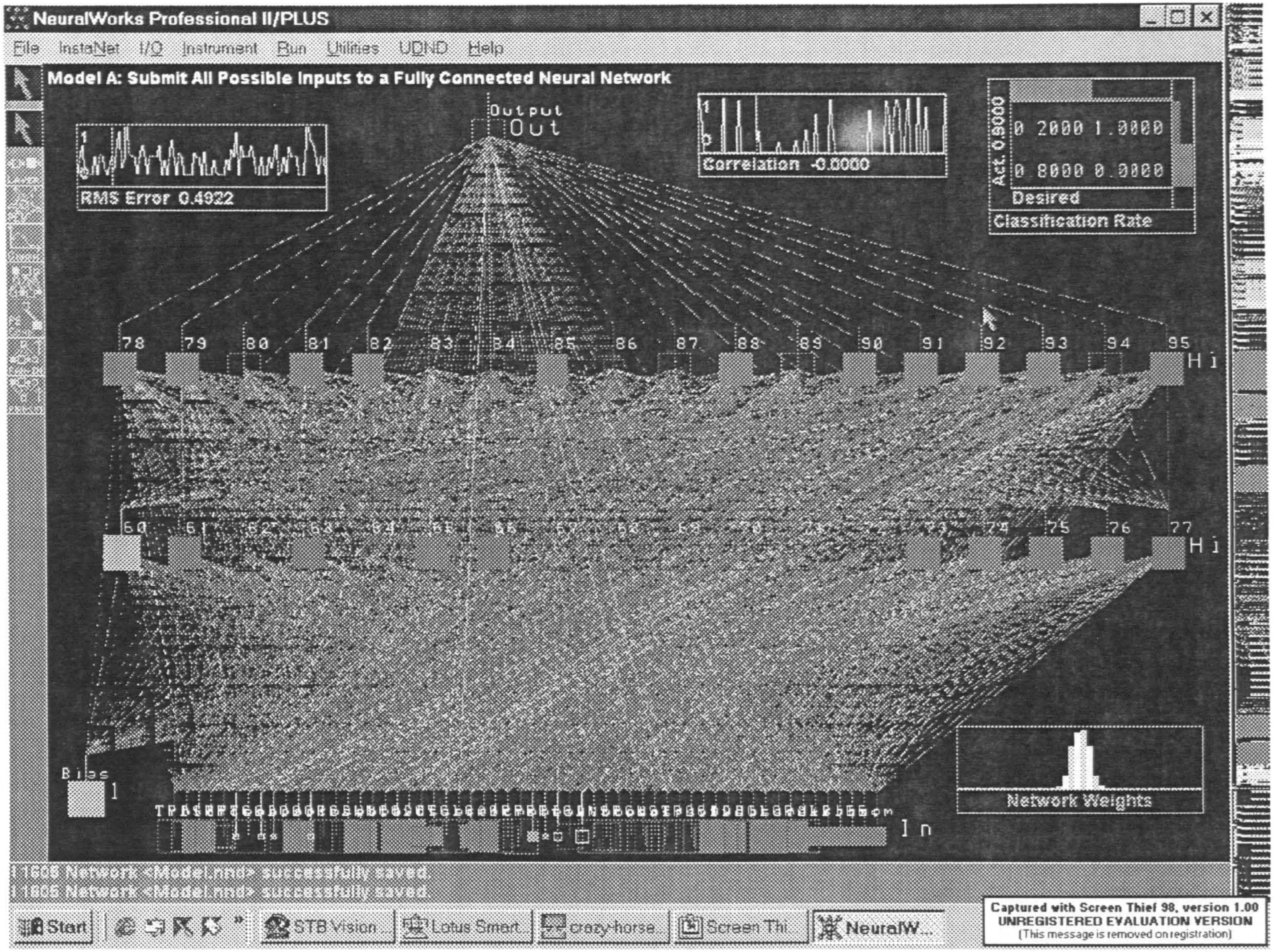
5


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
A Successfully Trained Kohonen Network
Act. 0.9533
0.0000 0.0000 0.9400
0.0200 0.9400 0.0200
0.9800 0.0600 0.0400
Desired
Classification Rate
0.7
0
RMS Error 0.1764
19
20
21 Out
4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 Kohonen
3 In
Bias 1
2902 Changed to directory <C:\NW2V530>
Start
STB Vision 95 ...
Lotus SmartCe...
Hotmail Inbox - ...
Screen Thief 98
Neura
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)

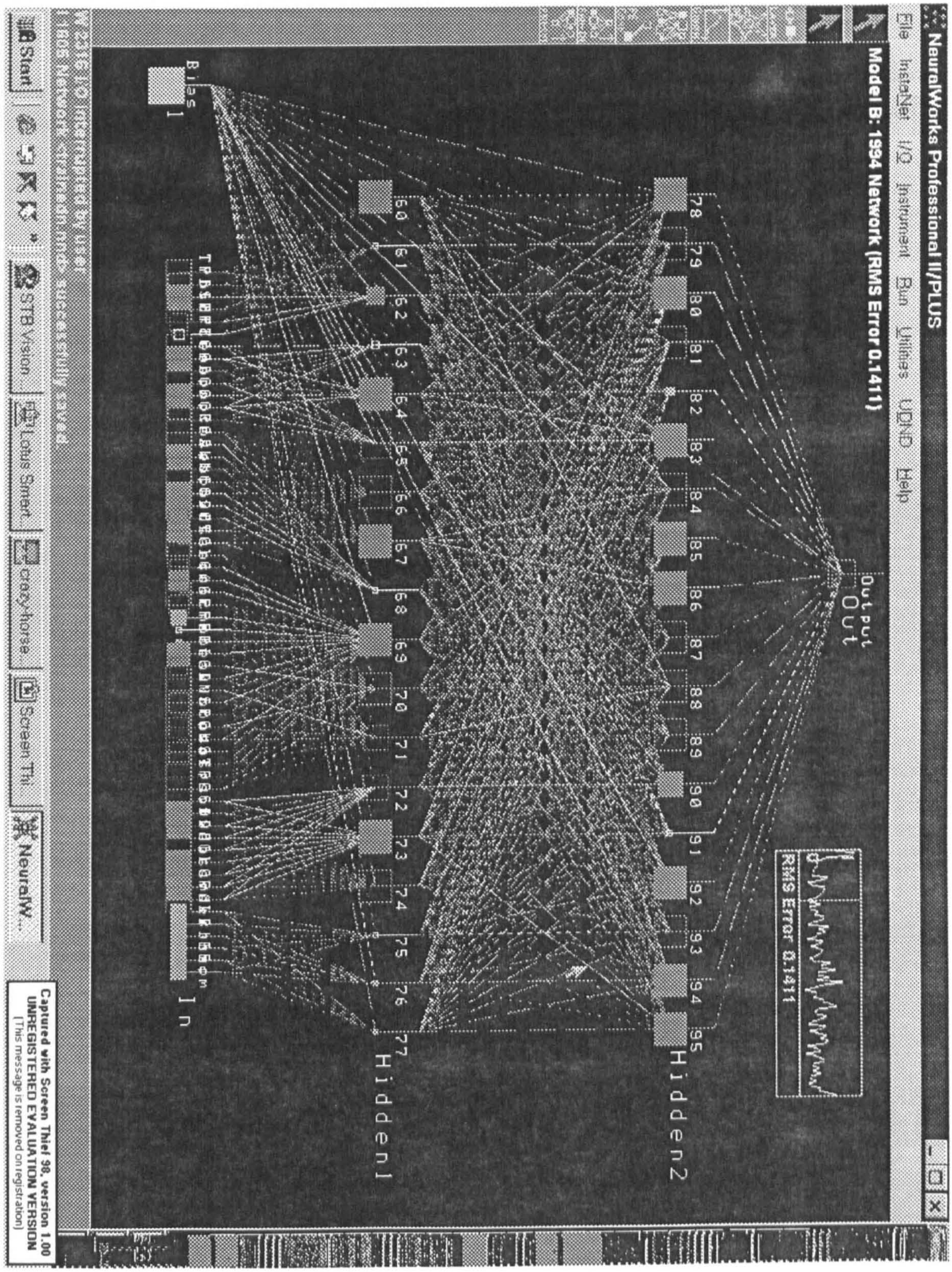

NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
A Bankruptcy Prediction Network
RMS Error 0.0115
Network Weights
Act. 0.3393
0.3214 0.0000
0.6786 0.0000
Desired
Classification Rate
Act. 0.0000
Desired
Conf. Matrix 1
24
Out
Correlation 0.0000
14 15 16 17 18 19 20 21 22 23
Hidden1
In
Bias
1
2902 Changed to directory <C:\NW2V530>
Start
STB Vision
Lotus Smar
Hotmail Inb
Screen Thi
NeuralW...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)

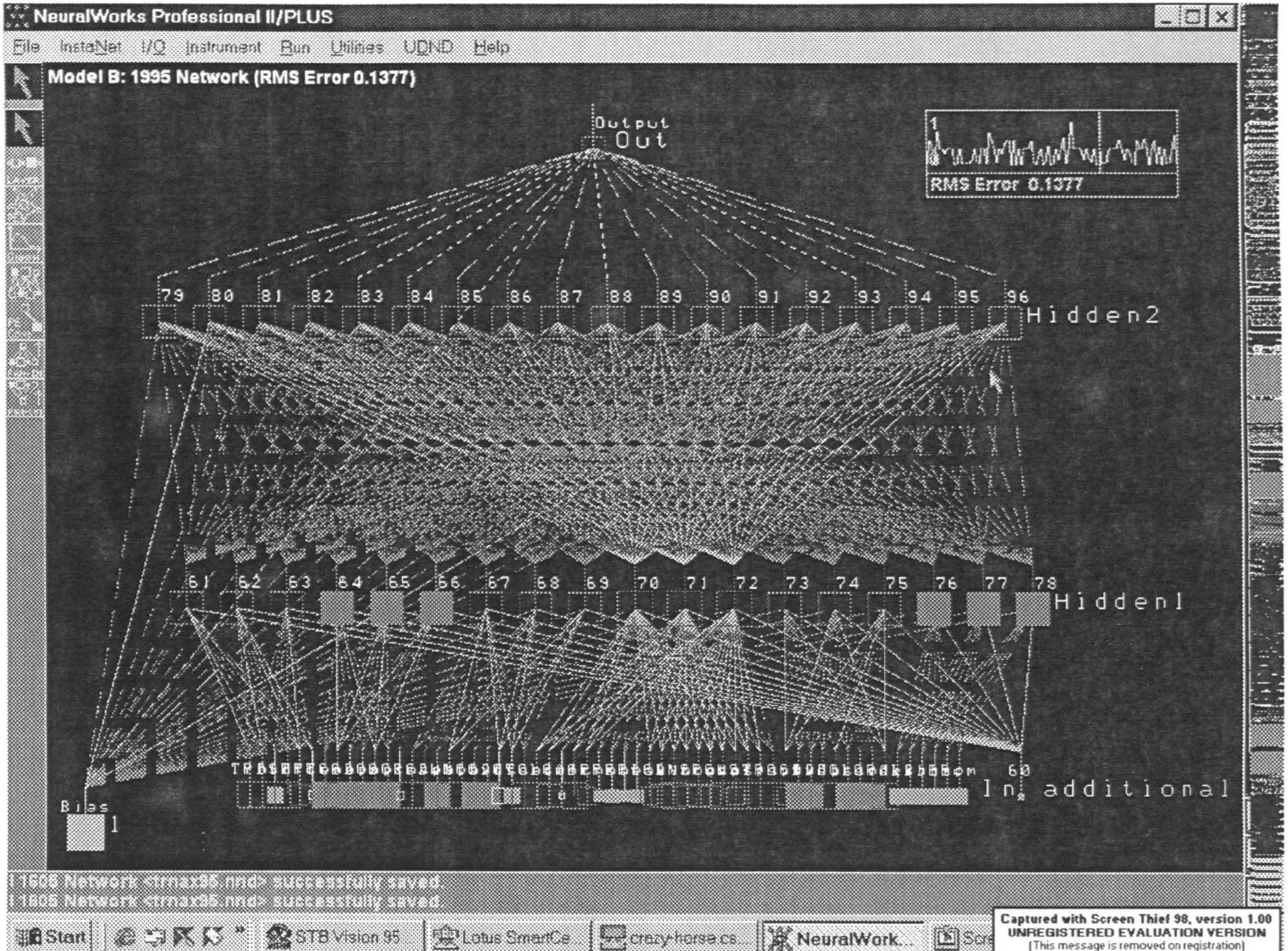


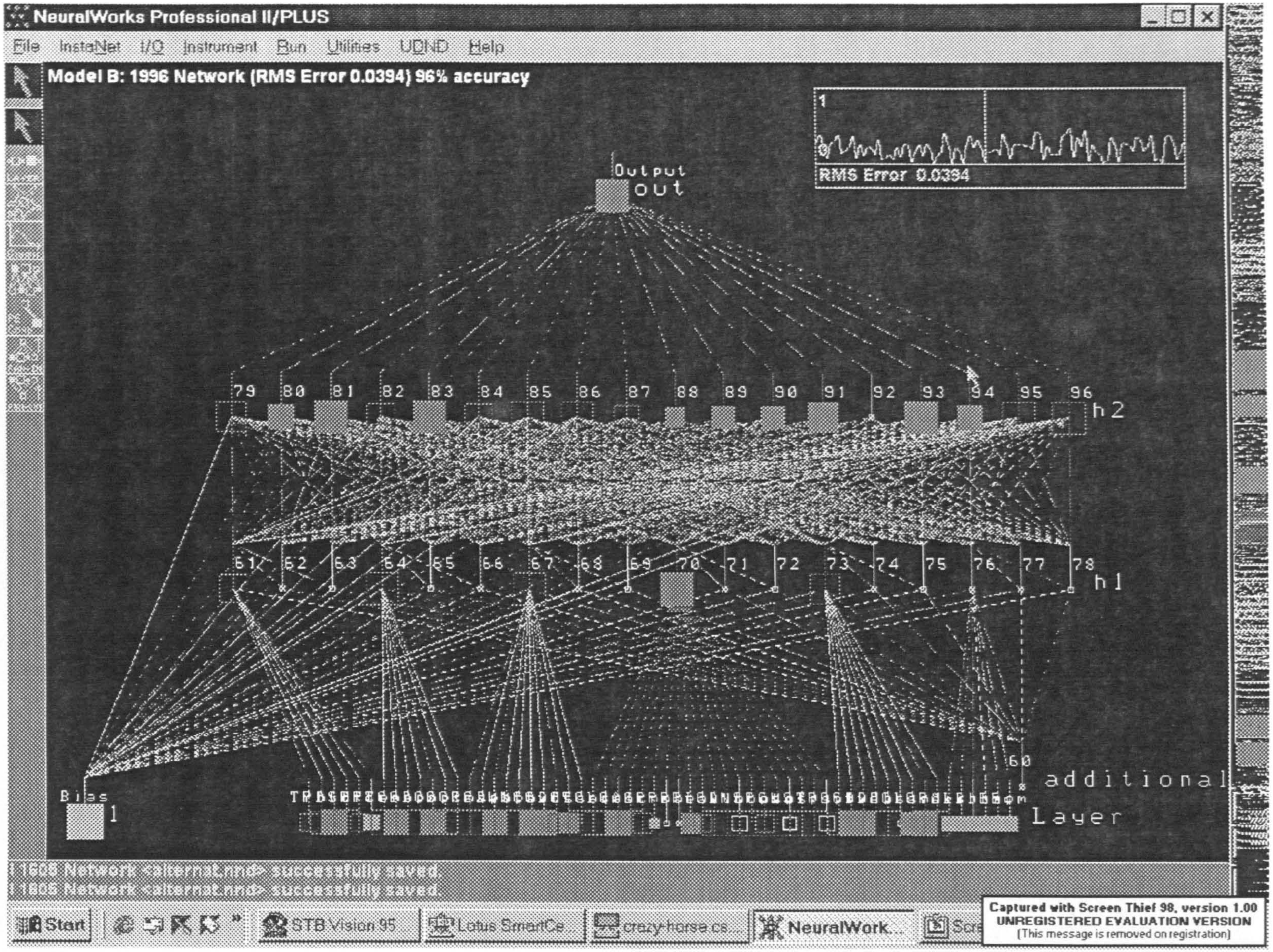
NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
My Pattern Classification Network
In
Category
I 2902 Changed to directory <C:\NW2V530\DPACK>
I 2902 Changed to directory <C:\NW2V530>
Start
STB Vision 95 ...
Lotus SmartCe...
Hotmail Inbox -...
Screen Thief 98
Neura
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)

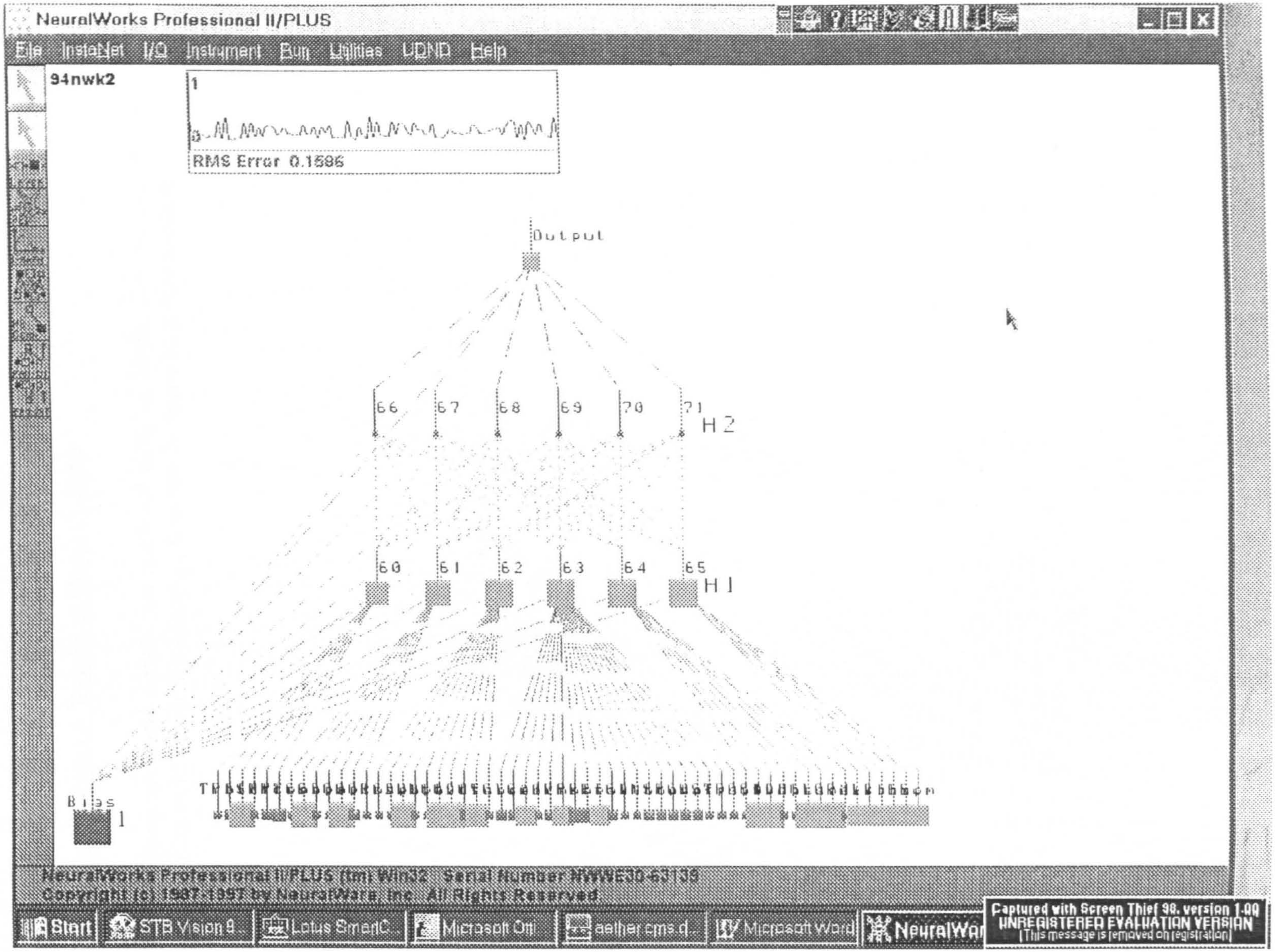


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
Model A: Submit All Possible Inputs to a Fully Connected Neural Network
RMS Error 0.4922
Output
Out
Correlation -0.0000
Act. 0.9000
0 2000 1.0000
0 8000 0.0000
Desired
Classification Rate
78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95
Hi
60 61
74 75 76 77
Hi
Bias
1
In
Network Weights
1606 Network <Model.nnd> successfully saved
1606 Network <Model.nnd> successfully saved
Start
STB Vision
Lotus Smart
crazy-horse
Screen Thi
NeuralW...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
Model B: 1994 Network (RMS Error 0.1411)
Output
Out
RMS Error 0.1411
Hidden2
Hidden1
Bias
In
Start
STB Vision
Lotus Smart
crazy-horse
Screen Thi
NeuralW...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
Model B: 1995 Network (RMS Error 0.1377)
Output
Out
RMS Error 0.1377
79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96
Hidden2
61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78
Hidden1
60
In additional
Bias
1
1605 Network <trmax95.nnd> successfully saved
1605 Network <trmax95.nnd> successfully saved
Start
STB Vision 95
Lotus SmartCe
crazy-horse.cs
NeuralWork...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
Model B: 1996 Network (RMS Error 0.0394) 96% accuracy
RMS Error 0.0394
Output
out
79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96
h2
61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78
h1
60
additional
Layer
Bias
1
Start
STB Vision 95
Lotus SmartCe...
crazy-horse.cs...
NeuralWork...
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)


NeuralWorks Professional II/PLUS
File InstaNet I/O Instrument Run Utilities UDND Help
94nwk2
1
RMS Error 0.1586
Output
66 67 68 69 70 71
H2
60 61 62 63 64 65
H1
Bias
1
NeuralWorks Professional II/PLUS (tm) Win32 Serial Number NWWE30-63139
Copyright (c) 1987-1997 by NeuralWare, Inc. All Rights Reserved
Start
STB Vision 9...
Lotus SmartC...
Microsoft Off...
aether cms d...
Microsoft Word
NeuralWar
Captured with Screen Thief 98, version 1.00
UNREGISTERED EVALUATION VERSION
(This message is removed on registration)

## Appendix I – Model A Results of Network Runs

The following are some sample test results of applying Model A to the test set. Recall that 20 network runs were carried for Model A, however, 9 outcomes are produced here.

RUN NO: FC1

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 40 | % healthy wrong | 60 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 88 | % bankrupt wrong | 2 | % bankrupt don't know | 10 |
| % Healthy right | 23 | % healthy wrong | 53 | % healthy don't know | 23 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 22 | % bankrupt wrong | 1 | % bankrupt don't know | 77 |
| % Healthy right | 17 | % healthy wrong | 23 | % healthy don't know | 60 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 8 | % bankrupt wrong | 1 | % bankrupt don't know | 92 |
| % Healthy right | 11 | % healthy wrong | 7 | % healthy don't know | 82 |

RUN NO: FC2

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 75000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 20000 | 15000 | 15000 | 15000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 6 | % bankrupt don't know | 0 |
| % Healthy right | 92 | % healthy wrong | 8 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 86 | % bankrupt wrong | 4 | % bankrupt don't know | 10 |
| % Healthy right | 76 | % healthy wrong | 1 | % healthy don't know | 23 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 21 | % bankrupt wrong | 3 | % bankrupt don't know | 76 |
| % Healthy right | 69 | % healthy wrong | 1 | % healthy don't know | 30 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 7 | % bankrupt wrong | 1 | % bankrupt don't know | 92 |
| % Healthy right | 64 | % healthy wrong | 1 | % healthy don't know | 34 |

RUN NO: FC6

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Cum-Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 34 | % healthy wrong | 66 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 88 | % bankrupt wrong | 2 | % bankrupt don't know | 9 |
| % Healthy right | 16 | % healthy wrong | 60 | % healthy don't know | 24 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 22 | % bankrupt wrong | 1 | % bankrupt don't know | 77 |
| % Healthy right | 11 | % healthy wrong | 30 | % healthy don't know | 58 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 8 | % bankrupt wrong | 1 | % bankrupt don't know | 92 |
| % Healthy right | 7 | % healthy wrong | 9 | % healthy don't know | 84 |

RUN NO: FC7

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 96 | % bankrupt wrong | 3 | % bankrupt don't know | 0 |
| % Healthy right | 50 | % healthy wrong | 50 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 74 | % bankrupt wrong | 0 | % bankrupt don't know | 25 |
| % Healthy right | 14 | % healthy wrong | 23 | % healthy don't know | 62 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 40 | % bankrupt wrong | 0 | % bankrupt don't know | 60 |
| % Healthy right | 8 | % healthy wrong | 13 | % healthy don't know | 79 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 19 | % bankrupt wrong | 0 | % bankrupt don't know | 81 |
| % Healthy right | 3 | % healthy wrong | 1 | % healthy don't know | 96 |

RUN NO: FC8

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Norm-Cum-Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 3 | % bankrupt don't know | 0 |
| % Healthy right | 51 | % healthy wrong | 49 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 74 | % bankrupt wrong | 0 | % bankrupt don't know | 25 |
| % Healthy right | 16 | % healthy wrong | 22 | % healthy don't know | 22 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 40 | % bankrupt wrong | 0 | % bankrupt don't know | 60 |
| % Healthy right | 9 | % healthy wrong | 12 | % healthy don't know | 79 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 19 | % bankrupt wrong | 0 | % bankrupt don't know | 81 |
| % Healthy right | 4 | % healthy wrong | 1 | % healthy don't know | 94 |

| | |
|---|---|
| RUN NO: | FC17 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Linear |
| LEARNING RULE | Delta |
| EPOCH SIZE | 18 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 49 | % healthy wrong | 52 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 60 | % bankrupt wrong | 0 | % bankrupt don't know | 40 |
| % Healthy right | 13 | % healthy wrong | 6 | % healthy don't know | 81 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 31 | % bankrupt wrong | 0 | % bankrupt don't know | 69 |
| % Healthy right | 7 | % healthy wrong | 4 | % healthy don't know | 89 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 14 | % bankrupt wrong | 0 | % bankrupt don't know | 86 |
| % Healthy right | 4 | % healthy wrong | 3 | % healthy don't know | 92 |

RUN NO: FC18

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE TanH

EPOCH SIZE 19

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.8 | 0.6 | 0.9 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 52 | % healthy wrong | 48 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 60 | % bankrupt wrong | 0 | % bankrupt don't know | 40 |
| % Healthy right | 18 | % healthy wrong | 6 | % healthy don't know | 77 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 31 | % bankrupt wrong | 0 | % bankrupt don't know | 69 |
| % Healthy right | 11 | % healthy wrong | 4 | % healthy don't know | 84 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 15 | % bankrupt wrong | 0 | % bankrupt don't know | 85 |
| % Healthy right | 7 | % healthy wrong | 3 | % healthy don't know | 90 |

RUN NO: 19

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Delta

EPOCH SIZE 19

ITERATIONS 150000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 50000 | 30000 | 30000 | 30000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 50 | % healthy wrong | 50 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 59 | % bankrupt wrong | 1 | % bankrupt don't know | 40 |
| % Healthy right | 16 | % healthy wrong | 8 | % healthy don't know | 77 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 30 | % bankrupt wrong | 1 | % bankrupt don't know | 68 |
| % Healthy right | 9 | % healthy wrong | 7 | % healthy don't know | 84 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 15 | % bankrupt wrong | 1 | % bankrupt don't know | 84 |
| % Healthy right | 6 | % healthy wrong | 6 | % healthy don't know | 89 |

RUN NO: FC20

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

| Classification Criteria | 0.50 and 0.50 | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 44 | % healthy wrong | 56 | % healthy don't know | 0 |

| Classification Criteria | 0.20 and 0.80 | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 59 | % bankrupt wrong | 1 | % bankrupt don't know | 40 |
| % Healthy right | 12 | % healthy wrong | 14 | % healthy don't know | 73 |

| Classification Criteria | 0.10 and 0.90 | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 30 | % bankrupt wrong | 1 | % bankrupt don't know | 68 |
| % Healthy right | 6 | % healthy wrong | 13 | % healthy don't know | 81 |

| Classification Criteria | 0.05 and 0.95 | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 15 | % bankrupt wrong | 1 | % bankrupt don't know | 68 |
| % Healthy right | 14 | % healthy wrong | 12 | % healthy don't know | 83 |

## Appendix J – Model B Results of Network Runs

The following are some sample test results of applying Model B to the test set. Recall that 64 network runs were carried for Model B, however, 31 outcomes are produced here.

TDN NO: 1

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Co | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rat | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolera | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Deca | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy 328 | | | | | |
| % Bankrupt right | 75 | % bankrupt wrong | 25 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy 328 | | | | | |
| % Bankrupt right | 65 | % bankrupt wrong | 15 | % bankrupt don't know | 20 |
| % Healthy right | 61 | % healthy wrong | 4 | % healthy don't know | 5 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.10 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy 328 | | | | | |
| % Bankrupt right | 54 | % bankrupt wrong | 13 | % bankrupt don't know | 33 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 10 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy 328 | | | | | |
| % Bankrupt right | 38 | % bankrupt wrong | 11 | % bankrupt don't know | 51 |
| % Healthy right | 86 | % healthy wrong | 1 | % healthy don't know | 13 |

TDN NO: 2

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 75000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 20000 | 15000 | 15000 | 15000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 78 | % bankrupt wrong | 22 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 71 | % bankrupt wrong | 14 | % bankrupt don't know | 15 |
| % Healthy right | 92 | % healthy wrong | 3 | % healthy don't know | 5 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 61 | % bankrupt wrong | 11 | % bankrupt don't know | 28 |
| % Healthy right | 90 | % healthy wrong | 1 | % healthy don't know | 9 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 44 | % bankrupt wrong | 10 | % bankrupt don't know | 46 |
| % Healthy right | 87 | % healthy wrong | 1 | % healthy don't know | 13 |

TDN NO: 3

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 250000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 50000 | 50000 | 50000 | 50000 | 50000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 82 | % bankrupt wrong | 18 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 76 | % bankrupt wrong | 13 | % bankrupt don't know | 11 |
| % Healthy right | 92 | % healthy wrong | 3 | % healthy don't know | 5 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 68 | % bankrupt wrong | 11 | % bankrupt don't know | 21 |
| % Healthy right | 91 | % healthy wrong | 1 | % healthy don't know | 9 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 51 | % bankrupt wrong | 11 | % bankrupt don't know | 38 |
| % Healthy right | 87 | % healthy wrong | 0 | % healthy don't know | 13 |

TDN NO: 4

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Linear

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.8 | 0.8 | 0.7 | 0.7 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 92 | % bankrupt wrong | 8 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 89 | % bankrupt wrong | 7 | % bankrupt don't know | 4 |
| % Healthy right | 93 | % healthy wrong | 3 | % healthy don't know | 3 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 82 | % bankrupt wrong | 6 | % bankrupt don't know | 13 |
| % Healthy right | 92 | % healthy wrong | 1 | % healthy don't know | 7 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 66 | % bankrupt wrong | 6 | % bankrupt don't know | 28 |
| % Healthy right | 87 | % healthy wrong | 1 | % healthy don't know | 12 |

TDN NO: 5

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Linear

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 150000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 20000 | 50000 | 20000 | 50000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | N/A | N/A | N/A | N/A | N/A |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 93 | % bankrupt wrong | 7 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 92 | % bankrupt wrong | 7 | % bankrupt don't know | 1 |
| % Healthy right | 93 | % healthy wrong | 3 | % healthy don't know | 3 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 86 | % bankrupt wrong | 6 | % bankrupt don't know | 8 |
| % Healthy right | 92 | % healthy wrong | 1 | % healthy don't know | 7 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 72 | % bankrupt wrong | 6 | % bankrupt don't know | 23 |
| % Healthy right | 87 | % healthy wrong | 1 | % healthy don't know | 12 |

TDN NO: 14

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 300000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 60000 | 60000 | 60000 | 60000 | 60000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | . 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 6 | % bankrupt don't know | 0 |
| % Healthy right | 71 | % healthy wrong | 29 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 83 | % bankrupt wrong | 3 | % bankrupt don't know | 15 |
| % Healthy right | 41 | % healthy wrong | 9 | % healthy don't know | 50 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 74 | % bankrupt wrong | 3 | % bankrupt don't know | 24 |
| % Healthy right | 31 | % healthy wrong | 2 | % healthy don't know | 67 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 63 | % bankrupt wrong | 2 | % bankrupt don't know | 35 |
| % Healthy right | 21 | % healthy wrong | 1 | % healthy don't know | 76 |

TDN NO: 24

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 500000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 100000 | 100000 | 100000 | 100000 | 100000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 94 | % bankrupt wrong | 6 | % bankrupt don't know | 0 |
| % Healthy right | 74 | % healthy wrong | 26 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 50 | % healthy wrong | 10 | % healthy don't know | 40 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 76 | % bankrupt wrong | 3 | % bankrupt don't know | 21 |
| % Healthy right | 41 | % healthy wrong | 4 | % healthy don't know | 54 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 65 | % bankrupt wrong | 2 | % bankrupt don't know | 33 |
| % Healthy right | 26 | % healthy wrong | 3 | % healthy don't know | 71 |

TDN NO: 25

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 40000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 5000 | 5000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 75 | % bankrupt wrong | 25 | % bankrupt don't know | 0 |
| % Healthy right | 95 | % healthy wrong | 5 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 67 | % bankrupt wrong | 15 | % bankrupt don't know | 18 |
| % Healthy right | 92 | % healthy wrong | 3 | % healthy don't know | 5 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 56 | % bankrupt wrong | 13 | % bankrupt don't know | 32 |
| % Healthy right | 90 | % healthy wrong | 1 | % healthy don't know | 9 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 39 | % bankrupt wrong | 11 | % bankrupt don't know | 50 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 13 |

TDN NO: 26

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 100000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 20000 | 20000 | 20000 | 20000 | 20000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 6 | % bankrupt don't know | 0 |
| % Healthy right | 76 | % healthy wrong | 24 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 84 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 53 | % healthy wrong | 9 | % healthy don't know | 38 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 76 | % bankrupt wrong | 3 | % bankrupt don't know | 22 |
| % Healthy right | 44 | % healthy wrong | 3 | % healthy don't know | 52 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 65 | % bankrupt wrong | 2 | % bankrupt don't know | 33 |
| % Healthy right | 28 | % healthy wrong | 2 | % healthy don't know | 70 |

| | |
|---|---|
| TDN NO: | 27 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Linear |
| LEARNING RULE | Norm-Cum-Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 83 | % healthy wrong | 17 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 85 | % bankrupt wrong | 2 | % bankrupt don't know | 13 |
| % Healthy right | 59 | % healthy wrong | 6 | % healthy don't know | 35 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 77 | % bankrupt wrong | 2 | % bankrupt don't know | 21 |
| % Healthy right | 49 | % healthy wrong | 3 | % healthy don't know | 48 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 66 | % bankrupt wrong | 2 | % bankrupt don't know | 32 |
| % Healthy right | 37 | % healthy wrong | 2 | % healthy don't know | 61 |

TDN NO: 28

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 95 | % bankrupt wrong | 5 | % bankrupt don't know | 0 |
| % Healthy right | 83 | % healthy wrong | 17 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 86 | % bankrupt wrong | 2 | % bankrupt don't know | 12 |
| % Healthy right | 65 | % healthy wrong | 6 | % healthy don't know | 29 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 77 | % bankrupt wrong | 2 | % bankrupt don't know | 20 |
| % Healthy right | 58 | % healthy wrong | 3 | % healthy don't know | 40 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 67 | % bankrupt wrong | 2 | % bankrupt don't know | 31 |
| % Healthy right | 44 | % healthy wrong | 2 | % healthy don't know | 54 |

TDN NO: 41

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Linear

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 81 | % bankrupt wrong | 19 | % bankrupt don't know | 0 |
| % Healthy right | 96 | % healthy wrong | 4 | % healthy don't know | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 63 | % bankrupt wrong | 11 | % bankrupt don't know | 26 |
| % Healthy right | 92 | % healthy wrong | 0 | % healthy don't know | 8 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.10 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 46 | % bankrupt wrong | 4 | % bankrupt don't know | 50 |
| % Healthy right | 84 | % healthy wrong | 0 | % healthy don't know | 16 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 46 | % bankrupt wrong | 0 | % bankrupt don't know | 54 |
| % Healthy right | 5 | % healthy wrong | 0 | % healthy don't know | 95 |

TDN NO: 42

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 500000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 100000 | 100000 | 100000 | 100000 | 100000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 86 | % bankrupt wrong | 14 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 75 | % bankrupt wrong | 10 | % bankrupt don't know | 15 |
| % Healthy right | 93 | % healthy wrong | 0 | % healthy don't know | 7 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 61 | % bankrupt wrong | 6 | % bankrupt don't know | 33 |
| % Healthy right | 85 | % healthy wrong | 0 | % healthy don't know | 15 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 61 | % bankrupt wrong | 0 | % bankrupt don't know | 39 |
| % Healthy right | 5 | % healthy wrong | 0 | % healthy don't know | 95 |

TDN NO: 43

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 88 | % bankrupt wrong | 13 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 81 | % bankrupt wrong | 10 | % bankrupt don't know | 10 |
| % Healthy right | 93 | % healthy wrong | 0 | % healthy don't know | 7 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 68 | % bankrupt wrong | 6 | % bankrupt don't know | 26 |
| % Healthy right | 85 | % healthy wrong | 0 | % healthy don't know | 15 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 68 | % bankrupt wrong | 0 | % bankrupt don't know | 32 |
| % Healthy right | 5 | % healthy wrong | 0 | % healthy don't know | 95 |

TDN NO: 44

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 100000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 20000 | 20000 | 20000 | 20000 | 20000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

TDN NO: 45

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 150000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 30000 | 30000 | 30000 | 30000 | 30000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 89 | % bankrupt wrong | 11 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 85 | % bankrupt wrong | 8 | % bankrupt don't know | 7 |
| % Healthy right | 94 | % healthy wrong | 0 | % healthy don't know | 6 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 74 | % bankrupt wrong | 4 | % bankrupt don't know | 22 |
| % Healthy right | 87 | % healthy wrong | 0 | % healthy don't know | 13 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 74 | % bankrupt wrong | 0 | % bankrupt don't know | 26 |
| % Healthy right | 7 | % healthy wrong | 0 | % healthy don't know | 93 |

| | |
|---|---|
| TDN NO: | 46 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Linear |
| LEARNING RULE | Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

TDN NO: 58

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 1000000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 200000 | 200000 | 200000 | 200000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 35 | % bankrupt wrong | 65 | % bankrupt don't know | 0 |
| % Healthy right | 96 | % healthy wrong | 4 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 33 | % bankrupt wrong | 14 | % bankrupt don't know | 53 |
| % Healthy right | 42 | % healthy wrong | 3 | % healthy don't know | 55 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 32 | % bankrupt wrong | 3 | % bankrupt don't know | 65 |
| % Healthy right | 32 | % healthy wrong | 2 | % healthy don't know | 65 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 28 | % bankrupt wrong | 2 | % bankrupt don't know | 70 |
| % Healthy right | 20 | % healthy wrong | 1 | % healthy don't know | 79 |

| | |
|---|---|
| TDN NO: | 59 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | Sigmoid |
| LEARNING RULE | Delta |
| EPOCH SIZE | 16 |
| ITERATIONS | 850000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 100000 | 100000 | 100000 | 100000 | 450000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 35 | % bankrupt wrong | 65 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 34 | % bankrupt wrong | 14 | % bankrupt don't know | 52 |
| % Healthy right | 43 | % healthy wrong | 3 | % healthy don't know | 55 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.10 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 33 | % bankrupt wrong | 3 | % bankrupt don't know | 63 |
| % Healthy right | 33 | % healthy wrong | 2 | % healthy don't know | 65 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 29 | % bankrupt wrong | 2 | % bankrupt don't know | 69 |
| % Healthy right | 20 | % healthy wrong | 1 | % healthy don't know | 78 |

| | |
|---|---|
| TDN NO: | 60 |
| SUMMATION FUNCTION | Sum |
| ERROR FUNCTION | Standard |
| NOISE | Uniform |
| TRANSFER FUNCTION | TanH |
| LEARNING RULE | Ext. BPB |
| EPOCH SIZE | 16 |
| ITERATIONS | 50000 |

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 75 | % bankrupt wrong | 25 | % bankrupt don't know | 0 |
| % Healthy right | 94 | % healthy wrong | 6 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 65 | % bankrupt wrong | 15 | % bankrupt don't know | 19 |
| % Healthy right | 91 | % healthy wrong | 4 | % healthy don't know | 5 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 54 | % bankrupt wrong | 13 | % bankrupt don't know | 33 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 10 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 38 | % bankrupt wrong | 11 | % bankrupt don't know | 51 |
| % Healthy right | 86 | % healthy wrong | 1 | % healthy don't know | 13 |

TDN NO: 61

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Linear

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 50000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 10000 | 10000 | 10000 | 10000 | 10000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.50 and 0.50 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 37 | % bankrupt wrong | 63 | % bankrupt don't know | 0 |
| % Healthy right | 98 | % healthy wrong | 2 | % healthy don't know | 0 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.20 and 0.80 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 35 | % bankrupt wrong | 14 | % bankrupt don't know | 51 |
| % Healthy right | 45 | % healthy wrong | 2 | % healthy don't know | 53 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.10 and 0.90 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 35 | % bankrupt wrong | 3 | % bankrupt don't know | 61 |
| % Healthy right | 36 | % healthy wrong | 2 | % healthy don't know | 63 |

| | | | | | |
|---|---|---|---|---|---|
| Classification Criteria | 0.05 and 0.95 | | | | |
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 31 | % bankrupt wrong | 2 | % bankrupt don't know | 67 |
| % Healthy right | 23 | % healthy wrong | 1 | % healthy don't know | 76 |

TDN NO: 62

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION Sigmoid

LEARNING RULE Delta

EPOCH SIZE 16

ITERATIONS 700000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 100000 | 100000 | 100000 | 100000 | 300000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 51 | % bankrupt wrong | 49 | % bankrupt don't know | 0 |
| % Healthy right | 98 | % healthy wrong | 2 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 49 | % bankrupt wrong | 11 | % bankrupt don't know | 39 |
| % Healthy right | 56 | % healthy wrong | 2 | % healthy don't know | 41 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 49 | % bankrupt wrong | 3 | % bankrupt don't know | 47 |
| % Healthy right | 49 | % healthy wrong | 2 | % healthy don't know | 50 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 46 | % bankrupt wrong | 2 | % bankrupt don't know | 52 |
| % Healthy right | 29 | % healthy wrong | 1 | % healthy don't know | 69 |

TDN NO: 63

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Cum-Delta

EPOCH SIZE 16

ITERATIONS 1000000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 200000 | 200000 | 200000 | 200000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

Training 1350
Test 400
Validation 750

Classification Criteria 0.50 and 0.50

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 96 | % healthy wrong | 4 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 94 | % bankrupt wrong | 3 | % bankrupt don't know | 3 |
| % Healthy right | 96 | % healthy wrong | 3 | % healthy don't know | 1 |

Classification Criteria 0.10 and 0.90

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 90 | % bankrupt wrong | 3 | % bankrupt don't know | 7 |
| % Healthy right | 95 | % healthy wrong | 2 | % healthy don't know | 4 |

Classification Criteria 0.05 and 0.95

| | |
|---|---|
| No of Bankrupt | 72 |
| No of Healthy | 328 |

| | | | | | |
|---|---|---|---|---|---|
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 89 | % healthy wrong | 1 | % healthy don't know | 10 |

TDN NO: 64

SUMMATION FUNCTION Sum

ERROR FUNCTION Standard

NOISE Uniform

TRANSFER FUNCTION TanH

LEARNING RULE Norm-Cum-Delta

EPOCH SIZE 16

ITERATIONS 1000000

GLOBAL LEARNING SCHEDULE

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Learning Count | 200000 | 200000 | 200000 | 200000 | 200000 |
| Temperature | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| Learning Rate | 0.9 | 0.9 | 0.8 | 0.8 | 0.9 |
| Momentum | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| Error Tolerance | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| Weight Decay | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Input Clamp | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Mod Factor | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| GAIN | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| RMS Error | | | | | |
| Hidden Units | 18 | 18 | 18 | 18 | 18 |

DATA

| | |
|---|---|
| Training | 1350 |
| Test | 400 |
| Validation | 750 |

Classification Criteria 0.50 and 0.50

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 96 | % bankrupt wrong | 4 | % bankrupt don't know | 0 |
| % Healthy right | 97 | % healthy wrong | 3 | % healthy don't know | 0 |

Classification Criteria 0.20 and 0.80

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 94 | % bankrupt wrong | 3 | % bankrupt don't know | 3 |
| % Healthy right | 96 | % healthy wrong | 3 | % healthy don't know | 1 |

Classification Criteria 0.10 and 0.90

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 90 | % bankrupt wrong | 3 | % bankrupt don't know | 7 |
| % Healthy right | 95 | % healthy wrong | 1 | % healthy don't know | 3 |

Classification Criteria 0.05 and 0.95

| | | | | | |
|---|---|---|---|---|---|
| No of Bankrupt | 72 | | | | |
| No of Healthy | 328 | | | | |
| % Bankrupt right | 85 | % bankrupt wrong | 3 | % bankrupt don't know | 13 |
| % Healthy right | 91 | % healthy wrong | 1 | % healthy don't know | 9 |

## Appendix J Author's CV

This section contains the author's CV which presents his highly successful banking and accounting experience in the domain.

## CURRICULUM VITAE


**Name:** **Mohammed Lateef Nasir**

**Address:** **43 Jarrom Court**
**Deacon Street**
**Leicester LE2 7EF**


**Target** **Senior Management and Policy Making**

### Profile

The author is a highly successful Chartered Banker and a qualified Accountant with extensive experience in bank lending to large companies and Corporation Tax Computations. He gained two years successful experience in corporation tax computations and business allowances and relief calculations before developing a progressive career in venture capital lending and stock trading. He has worked previously on the NIKKEI Index in Japan and on the Dow Jones in New York.

### Achievements

Associate member of the Chartered Institute of Bankers in England and Wales.
Associate member of the Chartered Institute of Chartered Company Secretaries.
Associate member of the Chartered Institute of Chartered Accountants in Nigeria.
Appointed examiner and reviewer for IEEE Transactions on Neural Networks.
Published ten external papers including IEEE Transactions.
Presented papers in prestigious conferences including IEEE.
Successfully implemented a Management Internal Controls Scheme for a large bank employing over 2000 staff.

### Capabilities

Internal Control Schemes for Global Risk Management.
Complex Venture Capital Lending and its associated Risks.
Full preparation of companies' financial statements.
Financial Statements disclosure requirements.
Corporate Lending, foreclosures, and assignments.
Reservation of title to goods procedures.
General Banking Operations.

**Work History**

| | |
|---|---|
| **1987-1989** | **National Bank of Nigeria Plc**<br>Complying with Bank's Internal Controls.<br>Cashiering.<br>Management and balancing of Bank's Waste Sheets.<br>Management of Exchange Controls Regulations. |
| **1990-1991** | **Chase Investment Bank: Nigeria**<br>Corporate Bank Lending and foreclosures.<br>Utilise knowledge of economic relationships to advise clients.<br>Develop methods and procedures to obtain needed data from clients for the purposes of lending and foreclosures.<br>Review and analyse clients' data for bank lending purposes. |
| **1991-1993** | **Chart Foulks Lynch PLC**<br>Examine clients financial records and corporate reports to attest their conformity with standards of preparation and reporting.<br>Prepare complex Corporation Tax Computations.<br>Consult on a number of matters, such as, revising the clients' the accounting systems to meet public disclosure requirements.<br>Conduct internal audits of all financial reporting requirements. |
| **1992-1994** | **The Chase Manhattan Bank, NA, New York and London.**<br>Developed new financial risk participation product to increase trade finance.<br>Establishing new lines of credit for trade finance.<br>Stock Brokerage.<br>Management of new financial assets.<br>Fund Management.<br>Units Trust Management.<br>Corporate Lending. |

**Education**

| | |
|---|---|
| Sept. 2000 | De Montfort University: Leicester, UK.<br>Ph. D. Corporate Failure Prediction Using Neural Networks. |
| June 1995 | De Montfort University: Leicester, UK.<br>MSc Accounting and Finance. – The Cost Control Approach to Improving Bank Profits. |
| June 1985 | City University: London UK.<br>BSc Accounting |

## Training

1994-1995 Have training on External Trade Credit Lines for overseas Trade and Finance.

## Military Training

1985 - 1986 Compulsory Youth Military Service (Youth Corps) in Nigeria.

## Civic Duties

Served as a technical juror on corporate fraud at the Old Bailey in London.
Served as a juror on fraud at the Southwark Crown Court.
Served as a juror on fraud at the Leicester Crown Court.

# DE MONTFORT UNIVERSITY

**MOHAMMED LATEEF NASIR**

has been awarded the degree of

**MASTER OF SCIENCE**

having followed an approved postgraduate programme in

**Accounting**

4th July 1995

**Kenneth Barker**
**Chief Executive and Vice-Chancellor**

**Dame Anne Mueller DCB**
**Chancellor**

E9500054\93095473



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Anne Mueller

**Dame Anne Mueller DCB**
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Kenneth Barker

**Kenneth Barker**
**Chief Executive and Vice-Chancellor**

Anne Mueller

**Dame Anne Mueller DCB**
**Chancellor**

E9500054\93095473



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**Good Luck for the future**
**Dr. Mohammed Lateef Nasir**